Context-Dependent Implicit Authentication for Wearable Device Users

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Abstract—As market wearables are becoming popular with a range of services, including making financial transactions, accessing cars, etc. that they provide based on various private information of a user, security of this information is becoming very important. However, users are often flooded with PINs and passwords in this internet of things (IoT) world. Additionally, hard-biometric, such as facial or finger recognition, based authentications are not adaptable for market wearables due to their limited sensing and computational capabilities. Therefore, it is a time demand to develop a burden-free implicit authentication mechanism for wearables using the less-informative soft-biometric data that are easily obtainable from the market wearables. In this work, we present a context-dependent soft-biometric-based wearable authentication system utilizing the heart rate, gait, and breathing audio signals. From our detailed analysis, we find that a binary support vector machine (SVM) with radial basis function (RBF) kernel can achieve an average accuracy of \(0.94 \pm 0.07\), \(F_1\) score of \(0.93 \pm 0.08\), an equal error rate (EER) of about \(0.06\) at a lower confidence threshold of \(0.52\), which shows the promise of this work.

Index Terms—wearable authentication, biometrics, implicit authentication

I. INTRODUCTION

A. Motivation

The interconnected nature of Internet of Things (IoT) have allowed us to remotely collect information or control multitude of physical objects. Along with the growth of IoT, advancements in smartphones and wearables in their sensing and computational capabilities to a point which enable many new applications and usage scenarios to emerge [1]–[5]. Even with this progress, wearables are still growing in popularity with the arrival of new applications. Some include the ability to identify a user to third party services [6], protect commercial customer information (i.e., passwords, credit card information) [7], manage financial payments, allows access to smartphones and other paired devices, unlock vehicles [7], monitor or track individuals (e.g., child or elderly monitoring or fall detection), and assess an individual’s health and fitness. According to a recent market report, a 72.7% increase in wearable shipments and an associated increase in sales revenue of 78.1% are predicted from 2016 to 2022 [8].

However, wearables also raise new challenges, especially in terms of security. The main accuracy and reliability concern is that imposters with unauthorized access can steal information from other sensitive IoT objects, which poses a significant risk [9]. Furthermore, an intentional device sharing between target and non-target users might lead to inaccurate and faulty assessment since healthcare providers and researchers are increasingly relying on wearables to monitor their patients or study participants remotely. Therefore, there is an imperative need for a robust and accurate authentication mechanism specifically for wearable device users.

Existing wearable devices either have no authentication systems or authentication mechanisms that are often knowledge-based regular PIN locks or pattern locks [7] [10], which suffer from scalability issues [11]. Additionally, many times, users opt to completely disable security mechanisms out of convenience, as the design hinders the implementation of security itself.

B. Related Work

1) Wearable Constraints: Wearable device user authentication is a relatively new field of research compared to other mobile authentication [6], [11]–[13]. The limited display sizes of wearables add another constraint that limits the choices of authentication mechanisms [6], [14]. But as technology advances companies such as Samsung, Fit-bit, Apple, Garmin, and Embrace can provide lower level granularity in data. More biometrics are available as more sensors are being added such as microphone, electrocardiograms (ECG), and GPS but there still hold accuracy concerns. Researchers have found that, although for people over the age of 85 Apple accurately detects atrial fibrillation at a rate of 96%, for people under 55 it only correctly diagnoses atrial fibrillation 19.6% of the time [15]. Another group of researchers [16] developed designed wrist strapped ECG reader and developed an authentication system with an accuracy of 93.5%, which is limited by the ease of use and the need for user movement. Therefore, an authentication scheme that can utilize data from a multitude of readily available sensors on market wearables could be more realistic to develop a non-stop implicit wearable device user authentication system.

2) Multi-modal Biometric Authentication: In previous work, combinations of biometrics were used to form multi-modal biometric authentication systems for increased reliability compared to unimodal systems, which often suffer from noisy data, intra-class variations, inter-class similarities, and spoof attacks [17]. For multi-modal authentication systems, researchers have utilized different hard- and soft-biometrics.
However, due to relatively low computational power of wearables, these multi-modal approaches are typically not implemented for implicit and continuous authentication on state-of-the-art wearables.

3) Wearable Authentication: Researchers recently proposed authentication techniques that are more suitable for wearables, focusing more on approaches based on behavioral biometrics, such as gait \cite{18}, \cite{20}, activity types \cite{6}, \cite{9}, gesture \cite{21}, keystroke dynamics \cite{22} and physiological biometrics, such as PPG signals \cite{23}. Almost all of these studies are based on project specific generated datasets. While other projects have addressed some of the limitations of gait-based approaches by considering different types of gestures \cite{21} or activities \cite{6}, \cite{9}. All of these models are based on movement and thereby, fail to work in the very common human state of being sedentary \cite{14}, \cite{22}. Authentication approaches using physiological biometric data, such as heart rate and bioimpedance \cite{13} require fine-grained samples and sensor readings are easily affected by noise, motion, etc but are constantly available. Depending on a user’s context, i.e., physical state and availability of biometrics it is possible to build a robust multi-modal authentication process, which is able to continue changing contexts.

C. Contributions

The main contribution of this paper is the exploration of a hierarchical non-stop implicit authentication for wearables using less informative coarse-grained soft-biometrics. Compared to previous work \cite{14}, \cite{24}, where we use hybrid-biometrics, such as calorie burn that can be affected by a user’s self-reported input, e.g., age, height, and weight, in this work we focus on three different soft-biometrics, i.e., heart rate, gait, and breathing that can be measured without a user’s self-reported input and can be easily obtained from the market wearables. In this work, we present a multi-biometric-based hierarchical context-driven approach (discussed in Section II-E) that works both in sedentary and non-sedentary periods. We develop both binary and unary models based on the availability of other people’s data in addition to a valid user’s data. We are able to authenticate a user with an average accuracy of $0.82 \pm 0.08$ & $F_1 = 0.81 \pm 0.08$ (non-sedentary, Table III) and an average accuracy $0.94 \pm 0.07$ & $F_1 = 0.93 \pm 0.08$ (sedentary, Table III), while developing the binary SVM models (Section III-D). While developing the unary models, we obtain an average accuracy of $0.72 \pm 0.07$ and $F_1 = 0.73 \pm 0.06$ (Sections III-D).

II. Approach

In this paper, we intend to demonstrate the importance and effectiveness of different biometrics to identify wearable device users with the help of different machine learning models. Before we describe the detailed analysis, we first introduce the datasets, pre-processing steps, feature engineering, and methods used in this work.

A. Datasets

In this work, we use the following three different datasets.

- **Fitbit dataset:** We use the heart rate data collected at a rate of one sample per minute using the Fitbit Charge HR device from 10 subjects similar to our previous work \cite{14}, \cite{24}–\cite{22}, \cite{22}–\cite{38}.
- **Gait dataset:** We use the WISDM dataset \cite{39}, where gyroscope and accelerometer readings were collected at a rate of one sample in 50 milliseconds using the LG G Watch (running Wear 1.5 operating system). In this work, we use 10 subjects’ data.
- **Audio dataset:** We collect breathing audio clips from 10 subjects with six distinct inhalation breathing events per clip using the Evistr digital voice recorder. The clips are around 5 seconds long.

B. Data Pre-Processing

Since we are using a real-world datasets, we first need to clean the dataset before using it. Then, we need to segment the continuous stream of biometrics, such as heart rate, gait information, and desired audio events (i.e., breathing). Finally, we compute and select influential features before constructing authentication models.

1) Data Segmentation: Since heart rate and gait data were sampled at different frequencies, therefore, we segment the heart rate and gait samples into 10-sample windows obtain stable and rich information. Using a 50% sliding window, we obtain 800 heart rate windows and 720 gait windows, i.e., instances from each subject. Unlike the heart rate or gait data, the audio data comes with other types of sounds in addition to desired breathing sounds. Additionally, some clips come with multiple breathing events separated by silence or noisy parts. Therefore, we segment the audio clips to fetch single inhalation breathing events. Thereby, we obtain around six inhalation breathing events per subject. Each event is modified in 102 ways mentioned in the next section (Section II-B2), we obtain a total of 612 instances from each subject. While utilizing the three different biometrics to develop different models discussed in the Methods section, i.e., Section II-E we consider the same 612 instances from each biometric.

2) Audio Data Augmentation: Breathing audio could be altered due to a change in contexts, e.g., environments, physical state, or mood. To simulate this and capture the variations, we augment the original audio breathing events using various pitch shifts and speed changes.

- **Pitch shift:** We consider 15 different pitch shifts ranging from -3.5 to 3.5 with 0.5 increments.
- **Speed change:** We consider seven speed changes ranging from 0.25x to 2x times the speed of an original clip with an increment of 0.25x, skipping 1x since that would represent the original clip, which we have already included as a pitch shift with value 0.
- **Noise Superposition:** We consider 10 randomly picked vacuum and washing machine sound clips, obtained from
the environmental sound classification dataset [40], as background noises to modify original breathing event clips with eight different signal-to-noise ratio levels ranging from $10^{-4}$ to $10^4$, incremented by magnitudes of 10 while skipping 1. Thereby, each original breathing clip is modified 102 times.

C. Feature Computation

We compute the following sets of candidate features.

- **Heart rate features:** From the windows of 10 samples we compute 21 statistical features described in our previous work [24].
- **Gait features:** We compute the same above mentioned 21 features from each window of x-, y-, and z-axis readings obtained from both gyroscope and accelerometer.
- **Audio features:** From each inhalation breathing event (original and augmented), we compute 40 Mel-frequency cepstral coefficients (MFCCs).

Thereby, we obtain 21 and 126 (21 from each of the six axes) features from a single window of heart rate and gait data, respectively, and 40 features from every breathing clip.

D. Feature Selection

To select the most influential features, we use the Sci-kit learn feature selection package “Select the $K$ Best Features” (SelectKBest), which provides an importance score for each feature and based on that score we rank the features. We try with different numbers of features, i.e., $K$, to find the best model performance. In this work, we find $K = 20$ performs the best. In each iteration of the leave-one-out validation, described in Section III-A, we select different feature sets, which are very similar with changes in ordering.

E. Methods

In Figure 1, we present an overview of our proposed implicit and continuous wearable-user authentication scheme using person-dependent multiple biometrics that are readily available on most of the wearables in the market. Depending on a user’s context, i.e., user’s state, various routes of the authentication scheme will be executed.

We first try to authenticate a user based on the heart rate obtained from the photo-plethysmogram (PPG) sensors since this biometric data is always available irrespective of a user’s state. However, the heart rate data may not be precised to identify the user when it is recorded in coarse-grained, e.g., one samples per minute. Additionally, the heart rate biometric can be easily affected by different factors, such as motion artifacts or stress. Therefore, if the system cannot authenticate the user with enough confidence, it checks the next authentication module that relies on other biometrics.

The authentication system first tries to check whether the user is moving utilizing the on-device accelerometer and gyroscope data. If the user is moving, the system tries to authenticate the user based on gait and heart rate biometrics together. If the system can authenticate the user with enough confidence, it allows the user to access the device.

However, if the user does not move or the gait and heart rate-based module cannot authenticate the user, the system tries to combine breathing biometrics collected from the on-device microphone. During sedentary states, audio recordings from wearables are less affected by motion artifacts. Thereby, the breathing audio recordings could be a good biometric to identify users, while during sedentary states. If the system can authenticate the user with enough confidence, it allows the user to access the device. Otherwise, the user’s access to the device is revoked and require some sort of external verification, such as pin locks or passwords.

Based on the combination of the three biometrics that we use in our authentication approach, we define the following models:

- Heart rate data-driven model (HR model)
- Heart rate and gait data-driven model (HRG model)
- Heart rate and breathing data-driven model (HRB model)

While developing the above models, we consider various classifiers, including the $k$-nearest neighbor ($k$-NN), random forest (RF), naive bayes (NB), and support vector machine (SVM) with binary and unary schemes. Compared to binary, unary models are available only for the SVM classifiers with radial basis function (RBF) kernels.

Based on the windowing approach discussed in Section II-B1, we can derive the time complexity of our authentication system based on the sampling frequency of different sensors. For example, let us consider a case where every heart rate sample is collected in $x$ seconds. With this sampling frequency, it will take $10^x$ seconds to make a window of 10 heart rate samples. Therefore, if the HR model can success-
### TABLE I: The best HR models with average and standard deviation of performance measures

| Classifier (parameters) | feature count | ACC          | RMSE         | FAR          | FRR          | $F_1$ score | AUC-ROC   |
|-------------------------|---------------|--------------|--------------|--------------|--------------|-------------|------------|
| RF (n estimators = 450) | 20            | 0.64 (0.12)  | 0.04 (0.01)  | 0.30 (0.15)  | 0.42 (0.16)  | 0.61 (0.14) | 0.64 (0.12) |
| k-NN (k = 32, minkowski distance) | 20            | 0.63 (0.11)  | 0.04 (0.01)  | 0.37 (0.15)  | 0.36 (0.14)  | 0.63 (0.12) | 0.63 (0.11) |
| NB                      | 20            | 0.65 (0.11)  | 0.04 (0.01)  | 0.36 (0.25)  | 0.39 (0.19)  | 0.61 (0.12) | 0.63 (0.11) |
| SVM (RBF kernel, $\gamma = 0.03$, $C = 3$) | 20            | 0.66 (0.11)  | 0.04 (0.01)  | 0.29 (0.16)  | 0.38 (0.17)  | 0.63 (0.14) | 0.66 (0.11) |
| SVM (Poly. kernel, $d = 4$, $C = 1$) | 20            | 0.65 (0.12)  | 0.04 (0.01)  | 0.26 (0.20)  | 0.44 (0.23)  | 0.59 (0.18) | 0.65 (0.12) |
| SVM (RBF kernel, $\gamma = 0.05$, $\nu = 0.5$) | 20            | 0.56 (0.08)  | 0.05 (0.00)  | 0.41 (0.14)  | 0.46 (0.09)  | 0.55 (0.08) | N/A        |

### TABLE II: The best HRG models with average and standard deviation of performance measures

| Classifier (parameters) | feature count | ACC          | RMSE         | FAR          | FRR          | $F_1$ score | AUC-ROC   |
|-------------------------|---------------|--------------|--------------|--------------|--------------|-------------|------------|
| RF (n estimators = 450) | 20            | 0.69 (0.13)  | 0.04 (0.01)  | 0.47 (0.32)  | 0.15 (0.21)  | 0.73 (0.21) | 0.71 (0.13) |
| k-NN (k = 24, minkowski distance) | 20            | 0.79 (0.07)  | 0.03 (0.01)  | 0.19 (0.10)  | 0.23 (0.09)  | 0.79 (0.08) | 0.79 (0.07) |
| NB                      | 20            | 0.65 (0.10)  | 0.04 (0.01)  | 0.28 (0.26)  | 0.42 (0.27)  | 0.62 (0.20) | 0.66 (0.10) |
| SVM (RBF kernel, $\gamma = 0.05$, $C = 5$) | 20            | 0.82 (0.08)  | 0.03 (0.01)  | 0.17 (0.09)  | 0.19 (0.10)  | 0.81 (0.08) | 0.82 (0.08) |
| SVM (Poly. kernel, $d = 3$, $C = 14$) | 20            | 0.78 (0.09)  | 0.03 (0.01)  | 0.19 (0.12)  | 0.25 (0.13)  | 0.77 (0.10) | 0.78 (0.09) |
| SVM (RBF kernel, $\gamma = 0.05$, $\nu = 0.5$) | 20            | 0.72 (0.10)  | 0.04 (0.01)  | 0.28 (0.16)  | 0.29 (0.08)  | 0.72 (0.09) | N/A        |

### TABLE III: The best HRB models with average and standard deviation of performance measures

| Classifier (parameters) | feature count | ACC          | RMSE         | FAR          | FRR          | $F_1$ score | AUC-ROC   |
|-------------------------|---------------|--------------|--------------|--------------|--------------|-------------|------------|
| RF (n estimators = 600) | 20            | 0.90 (0.07)  | 0.02 (0.01)  | 0.13 (0.10)  | 0.07 (0.08)  | 0.90 (0.07) | 0.90 (0.07) |
| k-NN (k = 2, minkowski distance) | 20            | 0.92 (0.07)  | 0.02 (0.01)  | 0.08 (0.07)  | 0.09 (0.11)  | 0.91 (0.09) | 0.92 (0.07) |
| NB                      | 20            | 0.75 (0.05)  | 0.04 (0.00)  | 0.22 (0.10)  | 0.29 (0.12)  | 0.75 (0.07) | 0.75 (0.05) |
| SVM (RBF kernel, $\gamma = 0.08$, $C = 4$) | 20            | 0.94 (0.07)  | 0.02 (0.01)  | 0.06 (0.07)  | 0.07 (0.09)  | 0.93 (0.08) | 0.94 (0.07) |
| SVM (Poly. kernel, $d = 4$, $C = 16$) | 20            | 0.91 (0.07)  | 0.02 (0.01)  | 0.06 (0.06)  | 0.11 (0.08)  | 0.91 (0.07) | 0.91 (0.07) |
| SVM (RBF kernel, $\gamma = 0.05$, $\nu = 0.5$) | 20            | 0.72 (0.07)  | 0.04 (0.00)  | 0.32 (0.10)  | 0.24 (0.06)  | 0.73 (0.06) | N/A        |

fully validate a user, it will take $10x$ seconds to complete the authentication process. However, if the HR models to validate a user, the system can take one of the two paths based on the user’s context. If the user is in a non-sedentary state, then the HRG model will be triggered, which will wait for an additional $10x$ seconds to collect 10 gait and heart rate samples; thereby, a total of $20x$ seconds will be required for the system to validate the user. If the HR model fails to validate the user and the user’s context, i.e., physical state is sedentary, then the system will try to authenticate the user based on breathing events in addition to heart rate. Since the average length of a breathing events used in this work is 1.4 seconds; therefore, if $x > 0.14$ seconds (i.e., a single heart rate window is longer than the breathing event), the system will need $10x$ seconds to gather 10 new heart rate samples for the HRB model to test the user. Thereby, it will take in total $20x$ seconds for the system to authenticate the user. However, if $x < 0.14$ seconds, i.e., breathing events are larger than the heart rate windows, the system will take $10x + 1.4$ seconds to validate the user.

### III. USER AUTHENTICATION

Before presenting the detailed evaluation of our models, we first present training-testing set split and our modeling schemes, followed by list of performance measures and hyper-parameter optimization.

#### A. Training-Testing Set

In our binary modeling, we try to distinguish a valid user (class-0) from the impostors (class-1). To avoid overfitting, we consider at least 10 times more feature windows, i.e., number of instances than the number of features. While training-testing, we follow the leave-one-out strategy, where we train-test $N$ unique models one-by-one for each user with $N$ number of instances. During each training-testing, we keep one instance for testing and use the rest of the $N − 1$ instances for training. Since we have 10 subjects and perform 10 leave-one-out testing for each subject; thereby, all aggregated performance measures presented in this paper are based on 60 performance measures.

For class balancing, in case of binary models, we consider the same $N − 1$ number of instances from each class. Since our imposter class (class-1) consists of nine person data (i.e., all subjects except the one considered as valid subject or class-0), we pick $(N − 1)/9$ instances from each imposter. For example, while training a HR model, we consider 510 heart rate windows from a target/valid user and 510/9 ≈ 56 windows from each of the nine imposters. In the test set, we consider 102 windows from the valid user and 102/9 ≈ 11 windows from each imposter. Similarly, while training a HRB model, we use 510 windows, i.e., breathing events
from a valid user in addition to 510 heart rate windows. Where, 510 breathing events are obtained from the five original breathing events and their 102 augmented events, i.e., \(5 \times 102 = 510\). To keep the training and test set separate, to use the remaining one breathing event and its 102 augmented events, i.e., 102 events/windows. For imposter, we uniformly select the windows to ensure a balanced classification. In case of unary models, we also follow the leave-one-out strategy. But, compared to the binary, unary models are developed with only a valid user’s data with an outlier rate (\(\nu\)) to split the user’s data into valid and outlier groups. In case of our experiments, we find \(\nu = 0.5\) as the optional outlier rate.

**B. Performance Measures**

To evaluate the performance of different modeling approaches, we consider the following measures:

**Accuracy (ACC)**, which is the fraction of predictions that are correct, i.e.,

\[
\text{ACC} = \frac{TP + TN}{TP + FN + FP + TN}
\]  

**Root Mean Square Error (RMSE)**, which is the square root of the sum of squares of the deviation from the prediction to the actual value. It is equivalent to the square root of the rate of misclassification, i.e.,

\[
\text{RMSE} = \sqrt{\frac{FP + FN}{TP + FN + FP + TN}}
\]

**False Acceptance Rate (FAR)**, which is the fraction of invalid users accepted by an authentication system, i.e.:

\[
\text{FAR} = \frac{FP}{FP + TN}
\]

**False Rejection Rate (FRR)**, which is the fraction of genuine users rejected by an authentication system, i.e.:

\[
\text{FRR} = \frac{FN}{TP + FN}
\]

**F1 Score**, which is the measure of performance of an authentication system based on both it precision (positive predictive value) and recall (true positive rate) measures, i.e.:

\[
F_1\text{Score} = 2 \left( \frac{TP}{TP + FN + \frac{TP}{TP + FP}} \right)^{-1}
\]

**Area Under the Curve - Receiver Operating Characteristic (AUC-ROC)**, which is the graphical relationship between FAR and FRR with the change of thresholds. Where terminologies used in Equations [1][2][3][4] and [5] have their usual meaning in machine learning, when classifying a subject using a feature set. Therefore, a desirable authentication system should have lower negative measures (i.e., RMSE, FAR, and FRR), but higher positive measures (i.e., ACC, F1 Score, and AUC-ROC) of performance. We also use **Equal Error Rate (EER)**, which is defined as the point when FRR and FAR are equal, i.e., a trade-off between the two error measures (i.e., FRR and FAR)

C. Hyper-Parameter Optimization

We use the grid search package in the Sci-kit learn to find the optimal hyper-parameter sets. For each leave-one-out modeling, we separately perform the hyper-parameter optimization using various ranges of values. From the different iterations of the leave-one-out approach, we obtain similar values for the hyper-parameters. In Tables I, II, and III, we present the set of optimal values obtained from different modeling approaches.

D. Authentication Model Evaluation

In Tables I, II, and III, we present the performance of the best models using various biometric combinations and different classifiers. In Table I we observe that the best binary HR model (i.e., model that only uses heart rate data) can provide an average ACC and AUC-ROC of 0.66 ± 0.11. As discussed previously in the Section [1][2][3][4][5] if the HR model is not confident enough to authenticate a user or fails to authenticate, we use additional biometrics, such as, gait or breathing sound. Compared to binary, for the unary HR model, we observe low performance, i.e., an average ACC of 0.56±0.08 since Unary model considers portions of a valid user’s data as outliers.
In Table II, we observe that adding gait biometric (when available) with heart rate, all measures improve. In case of the best binary HRG model (i.e., model that uses heart rate and gait biometrics), ACC and AUC-ROC increased by 24%; $F_1$ score increased by 29% compared to the best binary HR model. The FAR also improves (i.e., drops) from $0.29 \pm 0.16$ to $0.17 \pm 0.09$. Though gait data is only available while a user is moving, its addition to less accurate minute-level heart rate data can significantly improve authentication performance. Similarly to binary, the unary HRG model shows promise over the unary HR model with an overall increase of about 29% both for ACC and $F_1$ score.

In Table III we observe that the HRB model (i.e., model that uses heart rate and breathing biometrics) achieves a better performance compared to the HRG model. We achieve a 65% drop in the FAR while comparing the binary HRB with the binary HR model. Additionally, we observe $\approx 15\%$ increase, while comparing the ACC, $F_1$ score, and AUC-ROC of the binary HRB model with the binary HRG model. While comparing the HRB model to the HR model, we observe a huge performance improvement. Compared to the binary HR model, the binary HRB model performs better in terms of $F_1$ score (an increase of 48%) and AUC-ROC (an increase of 42%) with a high accuracy of $0.94 \pm 0.07$. The unary HRB model performs similar to the unary HRG model with a lower standard deviation, i.e., higher consistency, in terms of ACC ($0.10 \text{ vs. } 0.07$) and $F_1$ score ($0.09 \text{ vs. } 0.06$).

In Figure 2, we present five summarized values of different performance measures in addition to the average values presented in Table III. In the figure, we observe that median of each performance measure is better than average, since average is easily affected by outliers, which we do not show for the simplicity of visualization. For example, we obtain 2.6% better ACC, 2.8% better $F_1$ score, 59% better FAR, and 89% better FRR, while comparing median with average values. Additionally, we observe that the interquartile ranges of different performance measures are about 0.07 (Figure 2a) and 0.05 (Figure 2b). Similarly, in the case of unary modeling, we obtain tighter interquartile ranges. These narrow interquartile ranges represent the consistency of performance measures.

In Figure 3, we present the Probability Distribution Function (PDF) and Cumulative Distribution Function (CDF) with error bars of performance of the best binary model. In Figure 3, around 65% of the performance values (both ACC and $F_1$ scores) fall in the range of 0.95–1, which shows that our models perform very well for the most of the cases. In the case of unary modeling, we observe that $\frac{1}{3}$ (i.e., $\approx 66\%$) of the values fall in the range of 0.7–0.8, which is also a reasonable performance for unary model [24].

Additionally, in the figure, we observe that from the errors bars are very short, i.e., achieved performance values are highly consistent. Therefore, our developed models consistently perform well.

E. Error Analysis

In this section, we present an analysis on how our system performs with the change of confidence levels, i.e., thresholds. In case of an ideal system, it is desired to have a lower FAR and FRR. In Figures 4 we present our analysis of error rates (FAR and FRR) with varying confidence thresholds for the binary HRB SVM (RBF) model. We observe that at confidence threshold 0.52 FAR and FRR intersects with an equal error rate (EER) of about 0.06. After this point, error rates drop quickly. We observe that FAR and FRR drops below 0.05 after threshold values around 0.6 and 0.7, respectively.

IV. LIMITATIONS, DISCUSSION, AND CONCLUSIONS

To the best of our knowledge, this is the first work that attempts to authenticate a wearable device user without any explicit user interaction utilizing three easily obtainable soft-biometrics (i.e., heart rate, gait, and breathing sounds) in a more context-based approach, i.e., availability of data. We can authenticate a user with an average accuracy and AUC-ROC of $0.94 \pm 0.07$, $F_1$ score of $0.93 \pm 0.08$, and an EER of about 0.06 at 0.52 confidence threshold while considering the heart rate and breathing sounds. This shows the promise to develop a continuous implicit-authentication system for the market wearables utilizing their limited sensing and computational capabilities.

This work has some limitations, which we plan to address in the future. First, we have limited number of audio breathing clips. However, we increase the data volume using standard
audio augmentation approaches. Second, in this feasibility work, we use a set of ten subjects. However, we perform a leave-one-out validation approach and our achieved performance shows a promise to further investigate this with a large-scale extended period study. Third, we use different datasets, which could affect the performance. However, we use three independent biometrics and perform feature selection analysis to optimize implementation; thereby, our results potentially shows a baseline performance, which could further be improved by using the three biometrics from the same subject since that could more robustly identify a user compared to our case. Finally, more advanced modeling techniques such as deep learning models (recurrent neural networks or convolutional neural networks) may further improve the accuracy of the models, but that will require to off load data from the wearable, which can lead to additional security challenges; therefore, our approach has a higher scope to implement on the wearables.

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