Securing Sensitive Information in Smart Mobile Devices through Difficult-to-Mimic and Single-Time Usage Analytics

ABSTRACT

The ability of smart devices to recognize their owner gains attention with the advent of widespread sensitive usages of these devices such as storing secret and personal information. Unlike the existing techniques, in this paper, we propose a very lightweight single-time user identification technique that can ensure a unique authentication offering a near-to-impossible system to breach by attackers. Here, we have conducted a thorough study over single-time usage data gathered from 33 users. The study reveals some new findings, which in turn, leads us to a novel solution exploiting a new machine learning technique. Our evaluation confirms that the proposed technique operates as good as only 5% false acceptance rate (FAR) and only 6% false rejection rate (FRR). We further evaluate the performance measure through comparing its performance with some traditional machine learning techniques. Finally, we perform a real implementation of this technique as a mobile application to conduct a rigorous study in order to show how this technique works in practical situations. Outcomes of the study demonstrate as low as 1% FAR, which ensures extremely low false rate.

Keywords

Smartphone, Behavioral biometrics, Security, Mean-SD Clustering.

1. INTRODUCTION

The use of smartphones has changed dramatically over the last decade. Now, they are hardly been used for making phone calls, rather being used as a replacement for many electronic gadgets as well as non-electronic substances [1]. Their pervasive applications start including sensitive uses, for example, doing the bank transactions, storing sensitive data, financial activities, emails, etc., and people are frequently entrusting these devices with such secret personal information, which are prone to face attackers anytime. Consequently, the issue of identifying the owner of these devices to ensure the absolute security has become a prime concern in recent times.

According to the study presented in [2], even though people are concerned about the security issues of smart devices, they are uncomfortable using the available security techniques. The available user identification techniques can be divided into three fundamental categories [3], which are: (i) knowledge-based, (ii) object-based, and (iii) biometric-based. However, besides having their own drawbacks, all of these techniques can be a subject to burglary. Category (i) typically includes password or PIN system, which is inconvenient for users as they require memorizing. Furthermore, they can be stolen as easily as eavesdropping or shoulder surfing [4]. Object-based approaches usually rely on possession of token, which, if lost or stolen, imposters will get access to unauthorized data. Though biometric-based techniques rely on the uniqueness of physical/behavioral characteristics of a person, they can be easily mimicked or stolen by an intruder.

Recently, many studies have been performed exploring user identification based on usage monitoring. One such study conducted by [5] takes usage data and continuously performs authentication. Continuous authentications [5–8] keep authenticating current users thus gives more security against impostors. Such techniques require passwords or fingerprints or face-detections constantly, which makes these techniques not only resource-hungry but also very user-unfriendly (requiring passwords or security questions) [9, 10] or costly (requiring extra devices for face-detection or fingerprint). Therefore, a simple, single-time, easy-to-use, less resource-hungry user identification technique is yet to be discovered.

In this paper, we address this issue by introducing a new type of single-time, usage analytics based user identification technique. Taking into account two human behaviors—how the screen is being touched and how the device is being held—this technique exploits a new machine learning mechanism namely Mean-SD clustering. Here, we perform experiments with several machine learning approaches to evaluate the effectiveness of our considered human behaviors. We get high error rate for existing techniques. Therefore, we propose a new identification technique named Mean-SD Clustering to enhance the efficacy of our user identification task demanding limited resource. Our rigorous experimental evaluation confirms that mostly every user has a unique characteristics on touching the screen and holding the phone in combination, and consequently the user can be identified through these behavioral biometric. The strongest part of our proposed technique is that it exploits two behavioral metrics that are very difficult to mimic simultaneously. Therefore, it would be extremely hard for eavesdroppers to get access through breaching our proposed technique, which we confirm through getting zero false acceptance in our experimental evaluation.

Based on our work, we make the following set of contributions in this paper:

- We studied single-time usage data collected from 33 participants. Our analysis through unsupervised clustering reveals that most of the participants get dominated by individual clusters and most of the clusters dominate only one participant. This finding paves a foundation for further investigating the usage data for user identification.
- Next, we propose a novel light-weight machine learning technique called Mean-SD clustering for performing the user identification task.
- We confirm the efficacy of our proposed clustering technique through identifying users from our data set of 33 participants with as low as 5% False Acceptance Rate (FAR) and 6% False Rejection Rate (FRR). We perform necessary parameter tuning to achieve such low false rates. The false rates in combination are mostly lower compared to other available machine learning techniques that incur higher resource overhead.
- Finally, we implement our proposed technique in smartphones and perform user evaluation through the implementation. The user evaluation conducted under diversified situations and conditions demonstrates that the False Acceptance Rate gets to 1% even under attacks such as eavesdropping and shoulder surfing at an expense of higher False Rejection Rate, a less benign aspect compared to FAR.

The remainder of the paper is as follows: Section 2 covers related work and motivation of our work. Section 3 presents our proposed technique for user identification, which includes working methodology, data capturing, and user identification through clustering. Section 4 elaborates experimental design for evaluation of our proposed technique including experimental platform, developed application for data collection, and demography of the participants. In Section 5, we evaluate experimental data analysis. Section 6 makes comparative analysis over the performance of our proposed technique compared to either available machine learning techniques. Section 7 summarizes experimental findings. Section 8 presents outcomes of user evaluation through an implementation of our proposed technique is a smartphone. Finally Section 9 and 10 concludes the paper with pointing our future work.

2. RELATED WORK AND MOTIVATION

Traditional smartphone security system includes password or pin or pattern lock. Behavioral biometric techniques are also being used increasingly nowadays. All these techniques need memorizing except behavioral biometric technique. In addition to that, those techniques can be guessed or stolen as easily as shoulder surfing [11]. A study conducted on password based system [12] using keyboard layout, which can withstand shoulder surfing. However, this system still needs memorizing as well as strongly depend on keyboard layout of a specific language. Though behavioral biometric techniques, for example, fingerprints, cannot be guessed and give higher security but they can also be stolen or mimicked by imposters. Besides, they often require additional hardware, hence, can be costly. One such approach studied in [13], introduces an authentication system based on simultaneous face and voice recognition. Because of using two biometric characteristics, this system is hard to break. However, it requires too much resource as well as costly, therefore, not suitable for low-resource devices such as mobile devices.

The study in [14] is another example of behavioral biometric based system. It uses an additional identification layer immediately after password/pattern approach. Furthermore, another study [15] classifies users based on the usage of the user's hand movements while holding the device, and the timing of touch-typing when the user enters 4-digit PIN/password. Though both of these approaches gives high security, they are still vulnerable as they use passwords/PIN.

Two other studies [16] and [17] develop systems, which enhance the security. The study in [16] implements biometric analysis in combination with pattern recognition and [17] uses multi-touch gestures. However, this mechanism presents difficulties to users as it demands complex gestures.

Studies conducting on continuous authentication [5, 18, 19] perform user identification in the background continuously. Even though these systems give higher security, these are not suitable for deploying in low-resource devices as they are consuming more power and extremely resource-hungry.

In summary, conventional single-time user identification systems exhibit threat to being stolen or mimicked. The initial motivation for our research arose from the need to provide difficult-to-mimic user identification technique for mobile devices. Although continuous identification systems give more security, their strength depends on run-time data capturing and rigorousness of continuous data analyzing, which makes these unsuitable for low-resource devices as they consume significant CPU and memory. Therefore, the motivation of our work is to develop single-time user identification technique that would require tracking of user's usage only for one time. We chose to explore the use of user's touch and holding orientation based usage monitoring for identification since they usually have the benefits of not involving additional physical gadgets and not demanding the user's attention for a long period of time. Touch-based usage monitoring is free from the hassle of memorization. Alongside, another easily-capturable usage metric is holding orientation of a smartphone, which exhibits a good potential to vary user-to-user in a subtle way. To the best of our knowledge, combining the touch-based usage and holding orientations are yet to be investigated in the literature for user identification. Therefore, in this paper, we attempt to perform the investigation.

3. PROPOSED TECHNIQUE FOR USER IDENTIFICATION

In this section, we describe our proposed technique in details. Our working methodology involves two phases: training

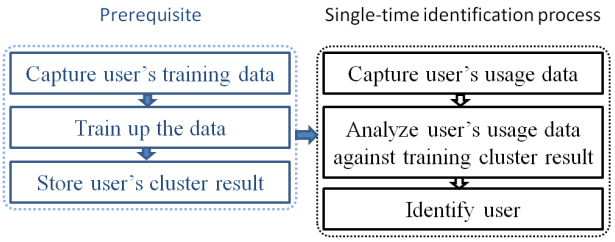


Figure 1: Methodology of our application

phase and user identification phase. The training phase is done only once. Based on the training result, user identification is performed. Two phases are elaborated in this section. First, we present the overview of working methodology along with the steps in training phase. Subsequently, we elaborate the user identification technique in details.

3.1 Overview of Underlying Mechanism

Our proposed technique requires training data, which is the core of the identification mechanism. The training data is collected from the user and immediately used to train the application. The training results are stored in the device, which will be used to perform the identification task. The training data will no longer be needed. After training, the system will be ready to identify its valid user. Identification starts by capturing usage data provided by the person who is using the device currently. This usage data then measured against the stored training data and provides a result. Based on this result, user identification is performed. Fig. 1 shows a block diagram of the proposed method.

3.2 Training Phase

Training phase includes two steps—collection training data and generating training result. This training phase occurs only once at the first time starting the application with the data given by the owner of the device. Later the device automatically identifies it's owner based on the result obtained from this training phase. The two steps are elaborated in the following subsections.

3.2.1 Collecting Data

Before designing our proposed technique, we studied user behavior based on touch usage. As a result of the study, we identified that we can extract 13 features from any user's touch usage. These 13 features individually do not show any significant characteristic that can specify a user. However, in combination, these features contribute to the unique identification of the user. These features are touch coordinates (start and end coordinates of swipe), finger pressures (the force applied) over the start and end finger positions, velocity over the swipe, hold-time (the duration of interval between the starting and ending of the swipe), tilt angle, and rotation matrix while pressing the button.

3.2.2 Training

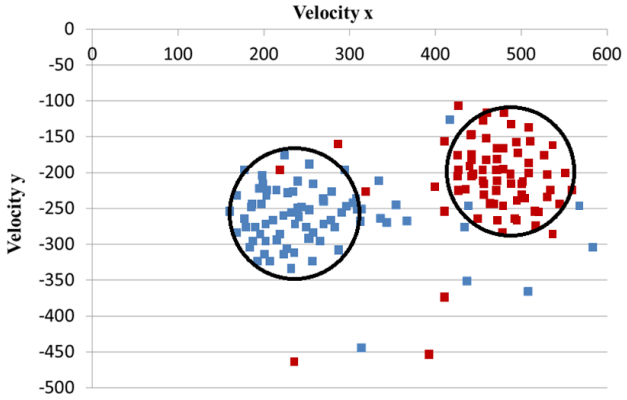


Figure 2: Proposed Mean-SD Clustering technique

As discussed before, each usage data contains 13 features, therefore, each data can be considered as a 13-dimensional vector. In the data collection phase, we collect such data sets from the user for training. Such sets of data for a specific user forms a cluster in 13-dimensional space. Consequently, we can say that in 13-dimensional space, data collected from each person forms separate clusters and therefore, they can be uniquely identified later if we know their cluster information. Our proposed solution identifies the cluster for each user by their cluster centroid, which is the mean of cluster members and cluster size. In the training phase, after collecting training data, the algorithm calculates the cluster information and stores in the device. The cluster size is varied and determined by taking a weighted sum of the average and standard deviation, which can be expressed by Eq. 1 presented as follows:

$$C = \left(M_{\text{avg}} \times W_{\text{avg}}\right) + \left(S_{\text{sd}} \times W_{\text{sd}}\right) \quad (1)$$

where M_{avg} represents average and S_{sd} represents the standard deviation of the cluster in training data. Besides, W_{avg} and W_{sd} are the weight of average and the weight of standard deviation of the cluster members respectively. Fig. 2 demonstrates the impression of such cluster size. Though in our case, the cluster will be in 13-dimensional space, here, we represent in 2D to make it visible in a simple manner. Only two features– velocity over the swipe along X-axis and along Y-axis–are considered in this figure. Velocity along X-axis is taken along X-axis, and Y-axis represents Velocity along Y-axis.

3.3 User Identification

User identification starts by collecting a single usage data of the current user. Similar to the earlier case, 13 features are extracted from this usage data. This data will indicate a point in the 13-dimensional region, which will be used to determine the user. From the training phase, we have the cluster centroid and the cluster size stored in the device, which represents the biometric characteristics of a user. The distance from the new point to the cluster centroid is calculated. The user

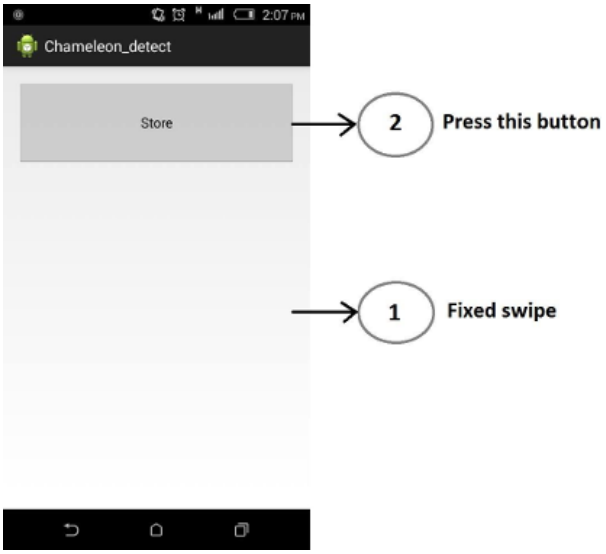


Figure 3: Screenshot of our application and step-wise tasks

is identified the owner if the new point falls into the cluster size. Otherwise, the user will be identified as a malicious user. Our proposed clustering technique identifies users based on their clusters, which are defined by their cluster centroid and size. The cluster size can be varied by the mean and standard deviation of the cluster. For this reason, we name our proposed technique as Mean-SD clustering.

3.4 Performance Metrics

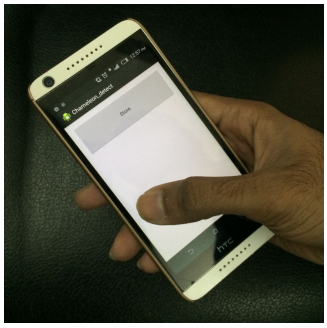
In the training phase, we used training data sets to calculate the cluster parameters. We collected training data sets from different users for this purpose. Therefore, we get multiple clusters where each cluster indicates a specific user. Similarly, test data sets are collected in order to evaluate the effectiveness of the training. The performance measure is determined by calculating False Acceptance Rate (FAR) and False Rejection Rate (FRR). The FAR indicates at what percentage the system inaccurately accepts an invalid user as a valid one. Similarly, FRR is the measure of the likelihood that the system will incorrectly reject a valid user. These two measures are the probability indicating how efficiently the system will perform.

4. EXPERIMENTAL DESIGN FOR EVALUATION OF OUR PROPOSED TECHNIQUE

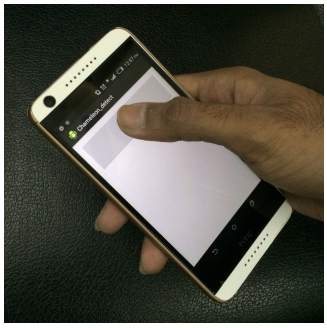
We perform a set of experiments in order to demonstrate the performance and accuracy of our proposed technique. Our experiments include data collection, analysis, implementing our proposed solution, and evaluating the results. In this section, we present the details of the experimental setup and demography of collected data.

4.1 Data Collection Platform

At first, we collected user's touch-based usage data in order to do the experiments. Data is to be collected from a device that has several sensors and a mechanism to store those. For this reason, we develop an Android application that captures and stores touch-based usage of a user. The Samsung Galaxy Young gt-s5360A [20] device is used for this purpose. With 384MB RAM of memory, the device possesses a processing capability of 832 MHz ARMv6 along with a Broadcom VideoCore IV. An Android application is developed in order to collect user's touch-based usage data.



(a) Task 1: Swipe over the touchscreen in a fixed pattern



(b) Task 2: Press a button over the touchscreen to store the swipe pattern

Figure 4: Data collection procedure in our experimentation

4.2 Application for Data Collection

As discussed in Section 3, our collected usage data should contain 13-features that are needed to train the application. For this purpose, our data collection application records usage patterns of different users from the perspective of all the 13 features. We developed the application in Android 2.3 (Gingerbread). The application asks the user to do two simple tasks—a fixed swipe on the touchscreen and then press a specific button. The screenshot of our application is presented in Fig. 3 along with the step-wise tasks. Furthermore, we present a user in action while using the application in Fig. 4.

Following the same process, we have collected data from several users. The demography of the participants is presented in the next section.

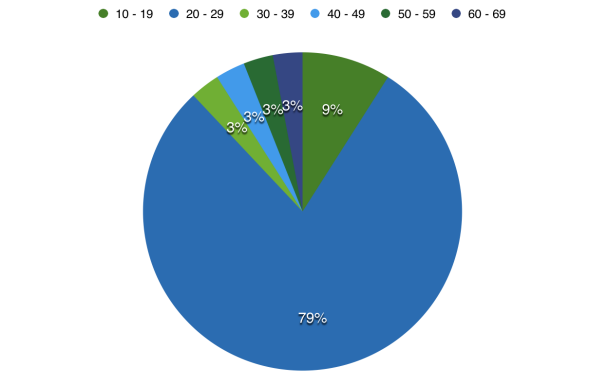
4.3 Demography of the Participants

For our experiment, we have collected touch-usage data from 33 participants using our android application. The users are selected from different age groups (from 11 to 67 years old), different genders (male and female), and different touch-screen usage experience (touch-screen device user and nonuser). Fig. 5 exhibits the demography of participants.

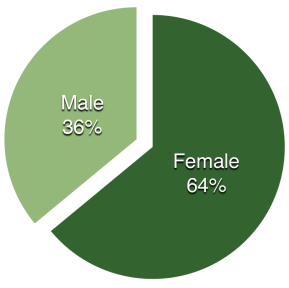
Fig. 5a shows the age diversity of our participants. Also, it exhibits that our participants are mostly youth having an age range from 20 to 30 years old. According to the survey studies existing in the literature [21] and [22], usage of touchscreen-based electronic devices show a largely skewed diversity in favor of the young generation. Following this, we have picked such skewed diversity in terms of age range. Also, a significant number of both male and female users have

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	4	4	5	7	0	6	0	4	0	0	2	0	5	0	0	0	6	3	0	0	0	2	0	0	0	0	0	2	0	0	0	0	2
3	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	1	0	0	0	0	0	0	0	4	1	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	1	0	0	0	1	0	0	0	0	0	0	1	4	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	2	0	0	0	0	0	0	1	0	0	6	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	1	0	0	0	5	1	0	0	4	4	0	0	0	0	0	0	7	0	0	1	3	4	0	0	0	1	0	0	0	0	0
13	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	6	0	0	1	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	1	4	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	1	0	0	0	2	2	0	0	0	1	0	0	1	0	0	0	0	0	1	3	1	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	1	0	3	2	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	0	2	0	1	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	7	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	3	0
26	0	2	0	0	0	0	0	0	0	0	0	0	0	3	0	0	1	0	0	0	0	0	0	2	3	2	0	0	0	2	4	1	5

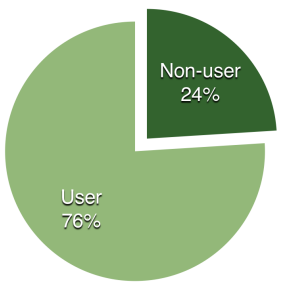
Table 1: Findings of unsupervised clustering of swipe patterns of the users (each row represents a cluster and each column represents a user)



(a) Age range (years)



(b) Gender



(c) Touchscreen usage

Figure 5: Demography of participants

participated in our study, showed in Fig. 5b. Lastly, Fig. 5c shows that we have collected usage data from both regular users of touchscreen electronic devices as well as non-users. From each participant, we collected 15 sets of touch usage data. Among them, we draw 10 sets of data for training and rest 5 sets for testing purpose. The drawing of the train and the test datasets are performed in several iterations in a random manner.

5. EXPERIMENTAL DATA ANALYSIS

At the beginning of our study, we conduct several experiments in order to understand the behavior of the experimental usage data collected from 33 users. At first, we perform unsupervised clustering and investigate the characteristics of generated clusters. The objective of applying unsupervised learning is to analyze whether there lies any user-cluster mapping for the extracted features. After that, we conduct a thorough analysis and investigate, if we can assign a user to a specific cluster and thus can identify the user as the original one and identify other users as aliens with newly-input test data from all the users based on the cluster characteristics. Furthermore, in the following subsections, we present our analytical outcomes along with how far we could reach the objectives.

5.1 Outcomes of Unsupervised Clustering

We attempt to cluster all the training data collected from all the users without providing the owner information of the data. An unsupervised clustering algorithm takes data having unknown properties and gather all the similar data together while separating the dissimilar data far from each other. Thus it creates clusters of related data, where each cluster members have diverse characteristics from other cluster members. We

find 26 clusters after applying the unsupervised clustering on our collected data. Note that, the number of clusters is close to the number of participants, i.e. 33. The result of this unsupervised learning is shown in Table 1. Here, each column of the table represents a user and each row denotes a cluster.

If we analyze the data presented in Table. 1, we can find that most of the rows in the table, i.e., clusters obtained by unsupervised clustering, is covered by a few columns, i.e., by a few of the participants. Besides, most of the participants cover only a few clusters, as most of the columns cover only a few rows. In the figure, both the blue and red shaded cells of the table exhibits the covering.

A bit more investigation reveals that most of the clusters are dominated by a very small number of users, and it is very close to 1 in most of the cases. Besides, most of the users dominate only a very small number of clusters, which is again very close to 1 in most of the cases. The dominances is represented in the table using red shaded cells.

From the above analysis, we can say that there might be a near one-to-one mapping between the users and the clusters of data. Consequently, it might be possible to efficiently cluster the data such that from the cluster information, the users could be identified.

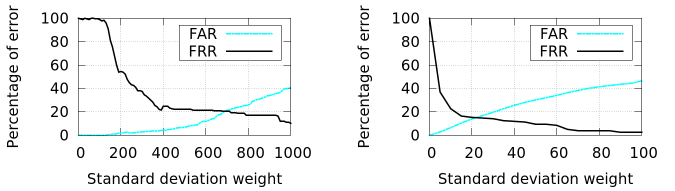
5.2 User identification using Mean-SD clustering

To perform an in-depth investigation of out proposed Mean-SD clustering over all of our collected data, we cluster the collected data from the perspective of both individual features and multiple features. We perform a number of iterations with such clustering tasks using randomly chosen sets of data for both individual features and all features. We perform these clustering tasks to lead towards efficient user identification. Moreover, we investigate the effect of allowing mismatch among the features in our identification process. We describe all the identification processes below.

5.2.1 Single Feature Identification

At first, we exploit the performance of our proposed algorithm based on each single feature. According to Eq. 1 presented in Section 3, the size of the cluster depends on two parameters—the weights of standard deviation and the weights of average. Here, we analyze the effects of single feature by varying the cluster size through changing only one parameter while keeping the other constant. Fig. 6a demonstrate the effects of changing only the weight of standard deviation keeping the weight of average fixed to 0. Similarly, the effect of changing only the weight of average keeping the weight of standard deviation fixed to 0 is demonstrated in Fig. 6b. Both Fig. 6a and Fig. 6b are pertinent for the feature of rotation about the Z-axis while pressing the button.

We further investigate the consequences of changing weights of average and standard deviation by analyzing their impacts on False Acceptance Rate (FAR) and False Rejection Rate (FRR). The individual impacts are displayed in Fig. 7. Fig. 7a demonstrates the effect of changing the weights on False Acceptance Rate for a single feature. Here, the feature of rotation about the Z-axis while pressing the button in our developed application is considered. This figure demonstrates that the False Acceptance Rate increases rapidly with an increase in the cluster size. Note that the cluster size can be increased through increasing either of the weights individually or both the weights simultaneously. Similarly, the effect of changing the weights on False Rejection Rate for a single feature is showed in Fig. 7b. However, in contrast to the previous case, in this case, the False Rejection Rate decreases with an increase in the cluster size.



(a) Effect of change in weight of standard deviation (while keeping the weight of average to 0)

(b) Effect of change in the weight of average (while keeping the weight of standard deviation to 0)

Figure 6: Effect of change in either the weight of standard deviation or the weight of average on False Acceptance Rate (FAR) and False Rejection Rate (FRR) for the feature of rotation about the Z-axis while pressing the button in our developed application

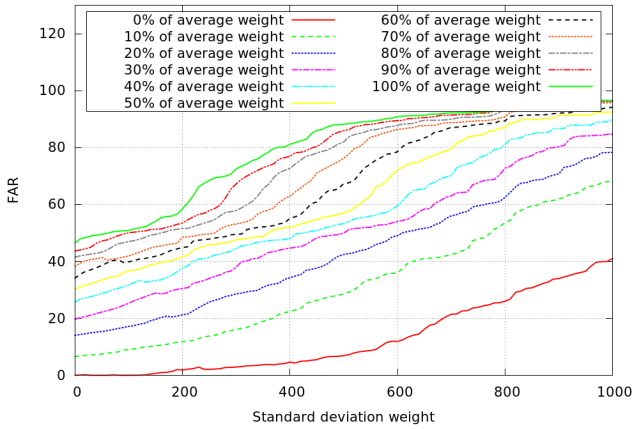
After analyzing the impacts of different possible values of the weights, we can find that the result obtained in the case of the feature of rotation about the Z-axis while pressing the button with the cluster size of $(AVG \times 5\% + SD \times 370\%)$ demonstrates the best possible accuracy. This best-possible result is presented in Fig. 7c. Here, the lowest value of FAR is 11% and the lowest value of FRR is 8%.

Following the same process, we compute FAR and FRR for each of the features. Fig. 8 shows the effects of changing weights of average and standard deviation on False Acceptance Rate and False Rejection Rate for each individual feature.

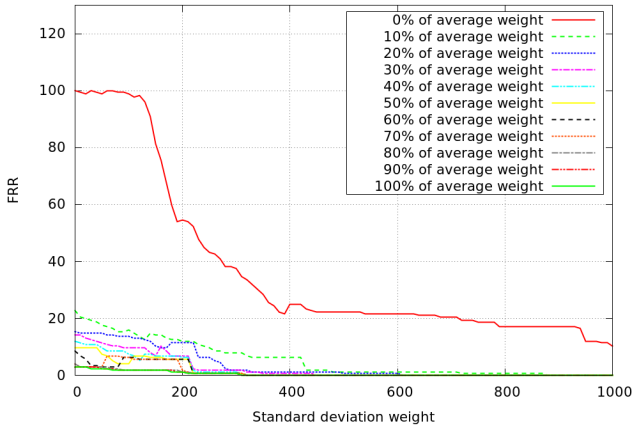
Note that, even though FAR and FRR vary for different features, all the values of FAR and FRR are highly significant. FAR and FRR for only one feature exhibit significant values rendering it not a feasible solution. Now, after reaching this extent, we apply the clustering technique to a different combination of features. Therefore, next, we present outcomes of user identification based on multiple features.

5.2.2 Multiple Features Identification

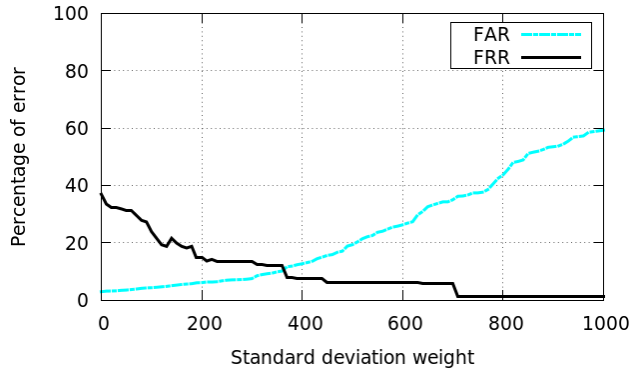
In addition to attempting to identify a user based on a single feature, we also attempt for the same identification task based on matching multiple features. The purpose behind such attempt is two-folded. Firstly, to improve the accuracy of identification. Secondly, to make the system more secure, as it is comparatively much more difficult for a malicious user to simultaneously mimic more than one behavior of the original user.



(a) Effect of change in the weight of average and the weight of standard deviation on False Acceptance Rate (FAR)

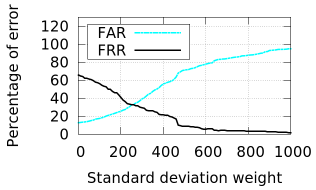


(b) Effect of change in the weight of average and the weight standard deviation on False Rejection Rate (FRR)

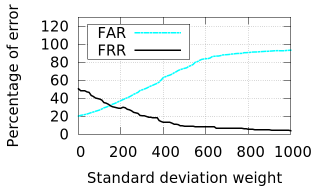


(c) False Acceptance Rate (FAR) and False Rejection Rate (FRR) for the feature providing the best-possible result

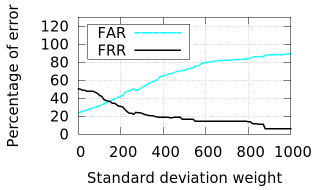
Figure 7: Effect of change in the weight of average and the weight of standard deviation on False Acceptance Rate (FAR) and False Rejection Rate (FRR) for the feature providing the best-possible outcomes, which is rotation about the Z-axis while pressing the button in our developed application



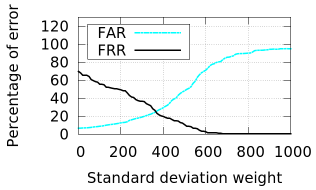
(a) X coordinate of the starting point used in swiping



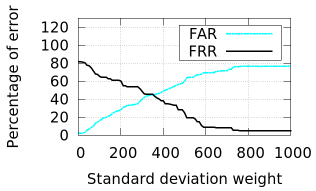
(b) Y coordinate of the starting point used in swiping



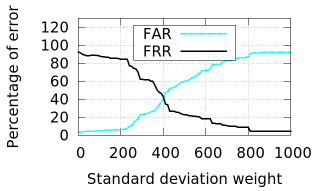
(c) X coordinate of the ending point used in swiping



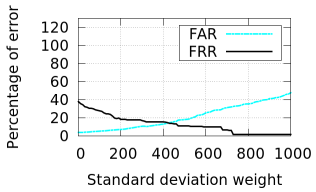
(d) Y coordinate of the ending point used in swiping



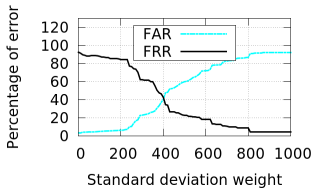
(e) Pressure on screen of the starting point used in swiping



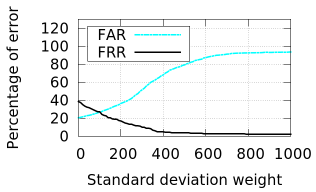
(f) Pressure on screen of the ending point used in swiping



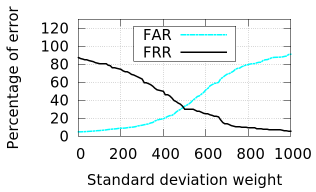
(g) Tilt angle while pressing the button



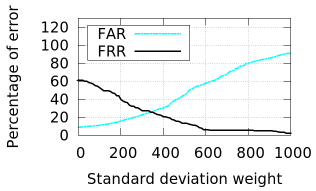
(h) Rotation about the x-axis while pressing the button



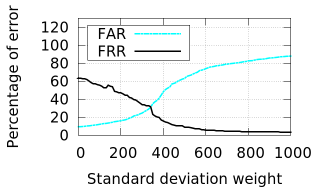
(i) Rotation about the y-axis while pressing the button



(j) X coordinate of velocity used in swiping

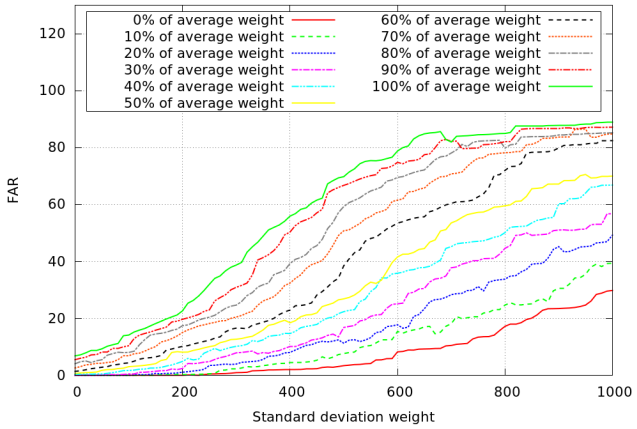


(k) Y coordinate of velocity used in swiping

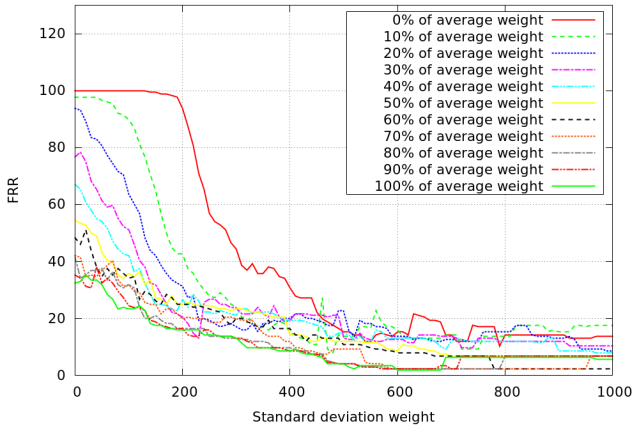


(l) Holding time for swiping

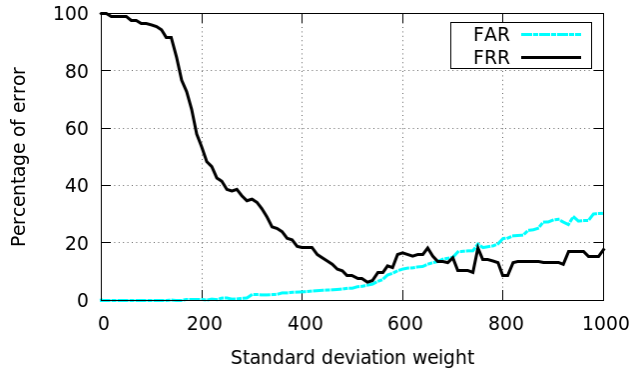
Figure 8: Effect of change in the weight of average and the weight of standard deviation on False Acceptance Rate (FAR) and False Rejection Rate (FRR) while considering single feature



(a) Effect of change in the weight of average and the weight of standard deviation on False Acceptance Rate (FAR)



(b) Effect of change in the weight of average and the weight of standard deviation on False Rejection Rate (FRR)



(c) False Acceptance Rate (FAR) and False Rejection Rate (FRR) while considering all the features providing the best-possible outcome

Figure 9: Effect of changing the weight of average and the weight of standard deviation on False Acceptance Rate and False Rejection Rate while considering all the features providing the best-possible outcomes

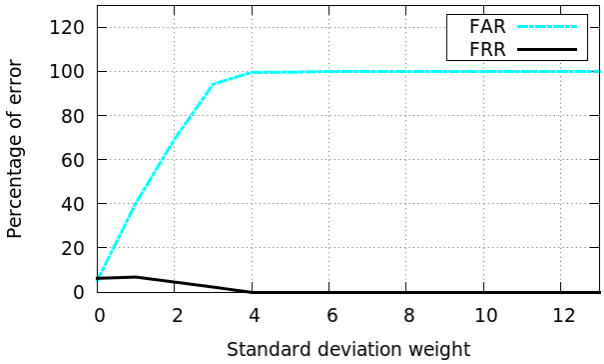


Figure 10: Effect of allowing mismatch considering all features

In our analysis based on multiple features matching, we utilize the same weight of average for all the features as well as the same weight of standard deviation for all the features. Similar to our previous analysis, here, we independently vary both the weights.

We present the effect of changing the weights of average and standard deviation on False Acceptance Rate for all features is clarified in Fig. 9a. Here, the finding is similar to that we have already found for a single feature. The False Acceptance Rate increases with an increase in the cluster size. Similarly, the False Rejection Rate decreases with an increase in the cluster size. Fig. 9b shows this result.

The best result obtained while considering all features in combination is for the cluster size of ($AVG \times 5\% + SD \times 530\%$). Fig. 9c presents variations FAR and FRR pertinent for this cluster size. Here, the best possible outcome provides only 5% FAR and 6% FRR.

Now, if we compare the results pertinent for considering only a single feature and the results pertinent for considering all features in combination, we can find some interesting observations. After analyzing Fig. 7a and Fig. 9a, we find that the FAR decreases if we consider all features in combination compared to the case of considering only a single feature. In the case of FRR, the scenario can get changed. Here, FRR may decrease if we consider only a single feature compared to the case of considering all features in combination. Fig. 7b and Fig. 9b present such a case of getting decreased FRR through considering only a single feature.

Even though we get two opposing trends in FAR and FRR while considering the features in isolation and while considering all the features in combination, we can achieve the best possible outcome in the case of considering all features in combination. Fig. 7c and Fig. 9c validates the phenomena of achieving the better outcome through considering all the features in combination.

5.2.3 *Allowing Mismatch over the Attributes*

Another important observation is related to allowing mismatch. We observed the result allowing mismatch on the best possible result for considering all features. Accuracy decreases while allowing mismatch of features. With the

increase in allowed mismatch, the FAR increases instantaneously from zero to 100% and the FRR decreases to zero. In fig. 10, the effect of allowing mismatch of features (0-12) is shown.

6. COMPARATIVE ANALYSIS OF CLASSICAL MACHINE LEARNING ALGORITHMS WITH MEAN-SD CLUSTERING

We analyze the outcome of collected experimental data with several classical machine learning algorithms. The objective of this analysis is to perform a comparative evaluation of the performance of our proposed solution against the performances of classical machine learning algorithms.

We choose three classical machine learning algorithms—k-Nearest Neighbor (k-NN) [23], decision tree [24], and a multiclass perceptron algorithm: Kessler's construction [25] considering their wide acceptability in the literature. We present the findings of these machine learning algorithms in Table 2.

Our experiments show that k-NN algorithm provides lower false rates compared to Decision tree and Kessler's construction algorithms. More specifically, the FRR is significantly higher for Decision tree and Kessler's construction compared to k-NN. Here, the FRR gets decreased for k-NN with decrease in the value of k. However, with decrease in the value of k, the FAR gets increased.

Table 2 also presents the running time needed to identify a user using the machine learning algorithms and also our proposed Mean-SD clustering technique. We can see that k-NN needs more execution time than other approaches. This is because for each test sample, k-NN checks against all the train samples and finds the best k matches. So, if we have M training samples each with dimension d, then k-NN algorithm needs O(Md) time to detect the class of a test sample. The time increases with the increase of train dataset. Where the other approaches only need a maximum of O(d) time. There is another significant drawback of using k-NN, which is, it consumes a large amount of memory as it stores the whole training dataset. Therefore, though k-NN has lower FAR and lower FRR, the large memory usage and longer execution time make it unsuitable for practical implementation. Decision tree algorithm also needs a large memory to store the whole tree information. Also, the FRR is too high in this case. Kessler's construction has the highest FRR among these approaches. Comparing with these classical machine learning algorithms, our proposed Mean-SD clustering technique provides the best result with 5% FAR, 6% FRR along with the lowest execution time and memory usage.

Algorithm	Parameter	FAR	FRR	Run-time
k-NN	k=1	1%	9%	$1.1e^{-4}$s
	k=3	1%	10%	$1.5e^{-4}$s
	k=5	0%	11%	$1.6e^{-4}$s
Decision tree		0%	16%	$1.94e^{-6}$s
Kessler		2%	41%	$2.04e^{-6}$s
Mean-SD		5%	6%	$1.6e^{-6}$s

Table 2: Comparative analysis of classical machine learning algorithms and our proposed technique

7. EXPERIMENTAL FINDINGS

This section describes the findings of our experiment. According to our experimental procedure, we get the following findings:

- Our experimental result of several Machine Learning algorithms is shown in Table. 2. We find higher FRR, though the FAR is a bit low.
- The experimental result of our proposed Mean-SD clustering demonstrates that the False Acceptance Rate increases rapidly with an increase in the cluster size and the False Rejection Rate decreases rapidly with an increase in the cluster size. These results are shown in Fig. 7a and Fig. 7b. The best possible accuracy of the result is obtained in the case of the feature of rotation about the Z-axis while pressing the button with the cluster size of ($AVG \times 5\% + SD \times 370\%$). Fig. 7c presents this best-possible results experiencing FRR is 8% and FAR is 11%.
- Our experiment discovers that relying on single feature is comparatively less secure as it is easy to mimic single feature as well as data may vary time to time for an individual user. Fig. 8 shows the low accuracy while considering a single feature.
- Our experimental result of considering all features is shown in Fig. 9c. The best result obtained while considering all features in combination is for the cluster size of ($AVG \times 5\% + SD \times 530\%$). Here, the best possible outcome provides only 5% FAR and 6% FRR.
- The experimental result of allowing mismatch on the best possible result for considering all features is shown in Fig. 10. Accuracy decreases while allowing mismatch of features.

8. USER EVALUATION

To evaluate the actual performance of our proposed technique, we have developed an Android application, which detects a user according to the *Mean-SD Clustering* algorithm as already discussed in this paper. For a specific user, the app initially takes training dataset from the user, which is the touch usage of the user for a number of times. This training dataset is used to train the device so that it can distinguish the user and other intruders. To our implementation, we set the tolerance level to two different values - 4% tolerance percentage of average value and 430% tolerance percentage of standard deviation. We set these values following our earlier findings.

To analysis the performance of our application with the presence of a different number of sensors, we use the following devices:

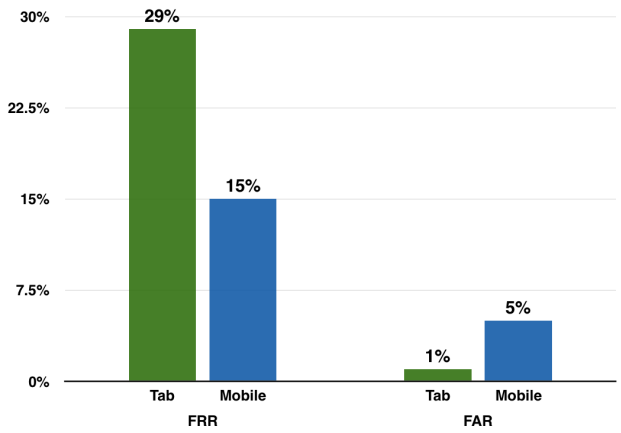


Figure 11: Performance measure of device with more sensors (tab) and device with fewer sensors (mobile)

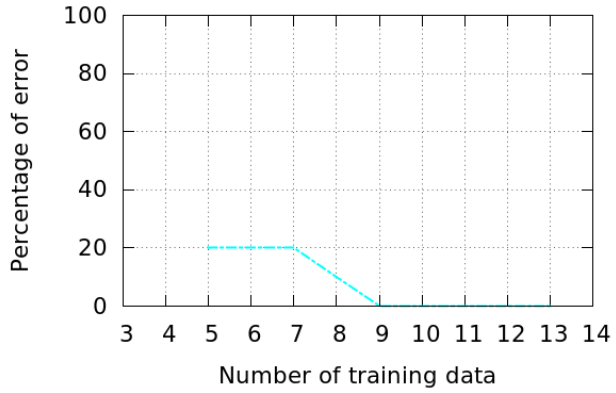


Figure 12: Performance measure with change of number of training data

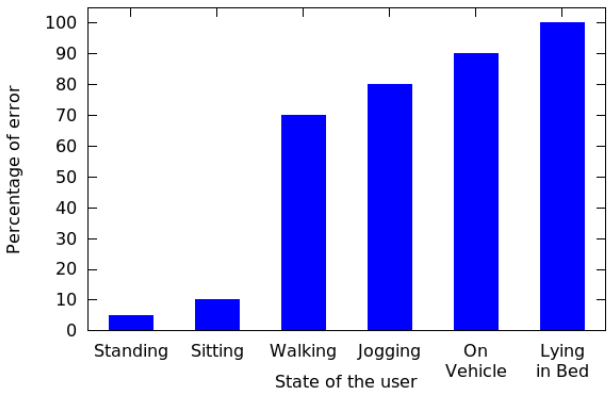


Figure 13: Performance measure for varying state of user

Samsung GALAXY Tab 10.1 LTE SC-01D: This device has Android version 3.2, dual-core 1.5 GHz CPU, and 1 GB RAM. Sensors for touch detection, finger movement velocity detection, and tilt angle detection were present in the device.

HTC Desire 626: This device has Android version 4.4.4, quad-core 1.2 GHz CPU, and 1 GB RAM. Sensors for touch detection and finger movement velocity detection were present in the device.

We let 23 users use our developed system. 20 of them were from the age range $20-29$ and 3 of them from the age range $30-39$. Besides, 22 of them were regular smartphone users. Alongside, 11 participants were male and 12 were female. 385 tests were performed in total on two devices and for different states of the user. The results obtained from two devices are demonstrated in Fig. 11. Recall that, among two devices, the mobile device has fewer sensors than the tablet device, therefore, they exhibit different performance. From the figure, we can see that the tablet device has extremely low FAR—1% only. On the other hand, the mobile device shows higher FAR (5%) though it shows lower FRR (15%) than the tablet device (29%). The main reason for this discrepancy is having an unequal number of sensors. As our solution totally depends on the sensors that capture 13 features from the hand movement of a user, it will perform poorly if it cannot capture the feature values because of the absence of sensors. That is why the mobile device has higher FAR but lower FRR. Therefore the tablet device, which has all the necessary sensors, represents the true performance measure of our proposed technique. It is worth mentioning that the False Acceptance rate retains the value 1.00% even for making an attempt through shoulder surfing. This ensures that the solution has a very high precision which is the prime motivation for this research.

We also have measured the accuracy rate for different training data which is shown in Fig. 12. It is found that by taking a minimum of 9 sets of data from the users in the training set, our system exhibits the maximum performance. Moreover, we have measured the accuracy while trying to enter the system in different states of the user. The result is shown in Fig. 13. It is found that the stationary states exhibit good performance except for the state of lying in the bed as this state changes the angular position of the device drastically.

The smartphone devices are used for storing various secure and important data of the user such as SSN or bank account information. For protecting such sensitive information where security break is not acceptable at all, our proposed technique is best suited as it has 0% False Acceptance Rate even when trying to mimic through shoulder surfing. False Rejection Rate indicates that, for every 3 attempts by the user, only one is falsely rejected. To ensure the security of such sensitive information, this FRR is acceptable as it gives the highest precision.

9. FUTURE WORK

The main purpose of our system is to identify a valid user of an electronic device and distinguish his/her from any other imposter. Here, we consider the usage of a user as a kind of

signature identification of that particular user. In our study presented in this paper, we have explored such identification based on single feature. In-depth analysis of multiple features in combination is yet to be done. This could add some more directions to improve performance of the user identification task, which we left as our future work. Besides, we intend to work at the kernel level of a device to enhance performance of identifying a user through following our proposed approach. This could unlock a vast area of observing a user's usages and make the identification system more robust. Additionally, in our system, we used Mean-SD clustering where the cluster size varies with the weights of average and standard deviation. We plan to explore other alternatives to calculate the cluster size in this regard.

10. CONCLUSION

As the usage of technology is increasing day-by-day, users often face the necessity of protecting their confidential and sensitive information from others. The first step for doing so is to identify valid and invalid users. Analyzing usage of electronic devices can facilitate such identification task. However, to the best of our knowledge, state-of-the-art technologies in this regard have focused on this important aspect of usage monitoring through either in a run-time manner requiring high system overhead and resources or through incorporating password/PIN that exhibits significant vulnerability under different types of security threats such as eavesdropping, shoulder surfing, etc.

Hence, in this paper, we propose a single-time user identification technique utilizing touch-based and holding orientation based usage monitoring. Here, we apply various existing machine learning approaches to carry out our user identification task. Those approaches offer relatively low-accuracy having significant resource usage, which indicates the necessity of a light-weight and high-accuracy approach. Therefore, we propose a novel clustering technique named Mean-SD clustering to perform our user identification task with high accuracy incurring low resource overhead.

We perform a set of rigorous experimental evaluation to validate the efficacy of our proposed user identification technique. The experimental results indicate that our proposed technique is highly accurate in user identification. Analyzing collected data from 33 users, we find that our technique can identify users with only 5% False Acceptance Rate and 6% False Rejection Rate. Here, we exploit our proposed light-weight clustering technique to confirm its implementation to be easy-to-implement and less resource hungry. The exploitation demonstrates that our proposed technique can be implemented in any off-the-shelf smartphone without the need of any additional hardware. We confirm the potency of our proposed technique to be implemented through developing its real implementation in an Android device. We demonstrate the efficacy of our proposed technique through letting 13 users use the implemented device. Usage of the users reveal that our proposed technique cannot be breached by intruders, i.e., FAR remains to 0%, even after making attempts through eavesdropping and shoulder surfing. Therefore, we envision that our proposed technique will offer a pervasive solution for user identification to mass users for touch-based electronic smart devices.

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