# A Machine Learning Approach for Medication Adherence Monitoring Using Body-Worn Sensors

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***Abstract*—One of the most important challenges in chronic disease self-management is medication non-adherence, which has irrevocable outcomes. Although many technologies have been developed for medication adherence monitoring, the reliability and cost-effectiveness of these approaches are not well understood to date. This paper presents a medication adherence monitoring system by user-activity tracking based on wrist-band wearable sensors. We develop machine learning algorithms that track wrist motions in real-time and identify medication intake activities. We propose a novel data analysis pipeline to reliably detect medication adherence by examining single-wrist motions. Our system achieves an accuracy of $78.3\%$ in adherence detection without need for medication pillboxes and with only one sensor worn on either of the wrists. The accuracy of our algorithm is only $7.9\%$ lower than a system with two sensors that track motions of both wrists.**

## I. Introduction

Medication adherence is the degree to which a patient follows the prescribed medications and their dosages [1]. Studies have demonstrated that medication non-adherence has negative impact on clinical outcomes and results in significant increase in health-care costs [2]. Prior studies have shown that over $50\%$ of the prescriptions has not been followed as instructed [1]. As a result, up to 70% of hospitalizations in United States is due to medication non-adherence [3], which costs the healthcare system $\$289$ billion each year [4].

Development of technological solutions for providing remote healthcare has emerged recently [5], [6]. Medication adherence and detecting medication intake has been one of the focuses of recent research in this area. Common approaches for medication intake monitoring include direct assessment methods such as blood test [7], patient-reported adherence assessment through smartphones [8], and pill-counting using wireless pillboxes [4], [9]. Such technologies are often expensive, subjective, and patient's compliance to use of these approaches is low.

Our goal in this paper is to develop an approach for seamless medication intake monitoring using wearable motion sensors. We utilize wrist-band sensors such as smart-watches with embedded accelerometers and gyroscopes to continuously track wrist movements. Our hypothesis is that the collective motions of wrist during medication intake is unique and can be accurately detected based on machine learning classification algorithms. Our data processing pipeline includes integration of feature selection and data fusion algorithms that allow us to detect medication intake even by tracking motions of one wrist.

**(a)** **(b)** **(c)** **(d)**

**Fig. 1:** Several medication adherence technologies: (a) PillPack (b) GlowCap (c) AdhereTech (d) PMD Service

## II. Motivation

Several examples of current medication adherence monitoring technologies are shown in Fig 1. PillPack [10] consists of a dispenser with a roll of packs of pills for a particular time. Each pack is labeled with the time and day, the pills are to be taken, and a list of all the pills in the particular pack. The price for PillPack is about $\$9$ on average. While it is simple and inexpensive, it still requires the person to be proactive and recall taking pills every day. Philips Medication Dispensing Service proposes a method for reminding patients to take their pill [11]. The price of this service is about $\$800$. It is not affordable for majority of the patients. Two other technologies that are similar to Philips Medication Dispensing Service are GlowCaps [12] and AdhereTech [13]. GlowCap uses a built-in mobile SIM to communicate with a local transmitter which notifies the patient, using a blinking light, to take the pill or refill. The cost for this device is $\$100$. AdhereTech can send a customized intervention and is helpful to specify the doses of prescriptions. It presently costs $\$60$.

We hypothesize that tracking wrist motions can be quite accurate in monitoring medication intake and inferring adherence versus non-adherence. The smaller motions of the wrists (e.g. opening the cap, taking pill from the bottle, taking the pill, closing the cap) form a logical sequence of motions that can be tracked using machine learning algorithms and therefore could be sufficient for monitoring medication adherence. The ultimate purpose of this study is to improve medication adherence without use of special pillboxes or as a complimentary technology that tracks wrist motions to ensure

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that the medication is taken. Another novel aspect of our work is that it predicts medication intake regardless of the location of the sensor on human body and the number of sensors.

## III. System Architecture and Data Analysis

In this section, the overall architecture of our system and the process of data analysis are described. For collecting data, we develop an android application that gathers data from gyroscope and accelerometer sensors in all three dimensions. In what follows, the process of system development and algorithm design is explained in detail.

### A. System Architecture

The motion monitoring technique that is developed in this paper is based on supervised learning methodologies. There are a number of methods for event classification in supervised learning research. Examples include rule based learner, probability based learner, decision tree based learner, etc. In this paper, we employ decision tree classifiers due to their simplicity and scalability. The proposed classifier predicts movements based on statistical features that capture trends in hand motions. Machine learning based methodology is a useful technique when we cannot extract a straightforward mathematical model for our problem or when building such a model is too expensive. The goal of this technique is to infer decisions based on a set of training data. The training process is defined as follows: (1) $X$ is a finite set of input features computed from the sensor readings; (2) $Y$ is a finite set of output labels associated with each input feature instance; (3) $F(X)$ is a function that maps input features to output labels.

The training data, $X$, is a set of input features, which will be explained in detail in the next section. The vector, $Y$, is a set of output labels indicating the actual motion scenarios during data collection. In this paper, the output labels are composed of five different scenarios that are defined based on common daily living movements. Given a set of input features $x_i$, $F(x_i)$ is a classification algorithm that generates an output label $y_i$ as the predicted scenario/action/label for $x_i$. The purpose of training is to find the mapping function from the input features to the output labels; therefore, if we feed a set of input features into our decision making function, it will provide a prediction of output label.

Our system consists of two sensor nodes for data collection and classifier training. Each person wears two android smart-watches on both hands. The collected sensor signals are segmented based on designated actions and repetitions. The trained model is then employed for motion monitoring purposes. An overview of the system is demonstrated in Fig 2.

### B. Data Collection and Analysis

As mentioned previously, an android application is developed to collect motion data by locally storing accelerometer and gyroscope readings and to transmit the data to a computer via Bluetooth connectivity.

*1) Data Collection:* In this study, 10 individuals with the age of 20-30 years participated in the data collection. For the purpose of recognizing medication intake, five different scenarios are considered. In particular, we include several scenarios with similar hand motions. Each scenario is repeated ten times by each participant. The labels are based on their relevance and irrelevance to pill consumption. The experimental scenarios include (1) Drinking water from the bottle; (2) Taking pill while sitting; (3) Taking pill while standing; (4) Writing; and (5) Eating. Our intention is to examine if the system is capable of differentiating between 'taking pill' and activities that may require a similar wrist motion such as 'drinking water'. The experimental scenarios are explained in more detail in Table I. Every action starts with the hand on the lap while sitting and by the side of the body while standing. Waiting periods of 1-2 seconds between each two repetitions and 10-12 seconds between each two scenarios are considered to allow manual segmentation of the signals during offline algorithm development.

*2) Signal Segmentation:* After transmitting the collected data to a computer, the data need to be segmented for preparation and formation of a training dataset with labeled activities. We developed a MATLAB tool to visualize the signals and label beginning and end of each activity scenario. Fig 3 shows one trial of each scenario for both hands from a randomly chosen trial and subject.

*3) Feature Analysis:* In order to develop a classifier, we need to form a training dataset. The training dataset is typically in the form a number of training instances in a feature space. Thus, we need to compute features that are most representative of the classification tasks (i.e., differentiating between medication intake activity and non-taken activities). We first extract an exhaustive set of features during 'Feature Extraction' process. These features are extracted from both sensors ('right' and 'left' wrists). The instances of both sensors are then combined to form a larger dataset with twice number of instances that exist in each sensor's training dataset. This resulting dataset is fed into a feature selection algorithm, forward feature selection, to select only most prominent features that are useful for the purpose of medication intake detection.

*4) Classifier Training:* The training data with labeled activities can be used to develop a decision tree classification algorithm. Constructing an optimal decision tree is the key problem in decision tree classifier. In general, many decision trees can be constructed from a given set of features. While some of the trees are more accurate than others, finding the optimal tree is computationally infeasible because of the exponential size of the search space. We use information gain provided by each feature to identify decision rules at each

**TABLE I:** Sequence of movements for each experimental scenario.

| **Sce.Id** | **Description** |
|---|---|
| **1,2,3** | lifting, opening, drinking, closing, placing it on table |
| **4** | lifting pen, opening, writing, closing, placing it on table |
| **5** | lifting pack, taking chocolate, eating, placing it on table |

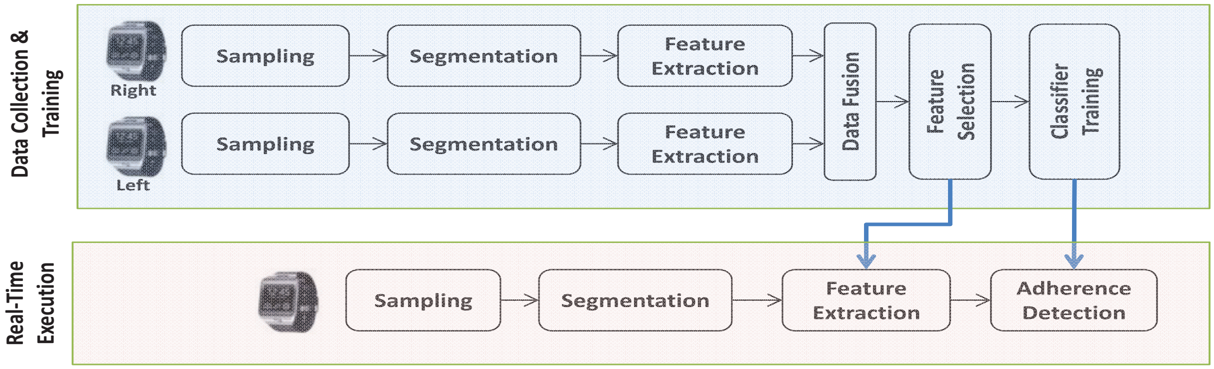



**Fig. 2:** Data processing flow: the system is initially trained using a set of training instances; then the model is used for future predictions.

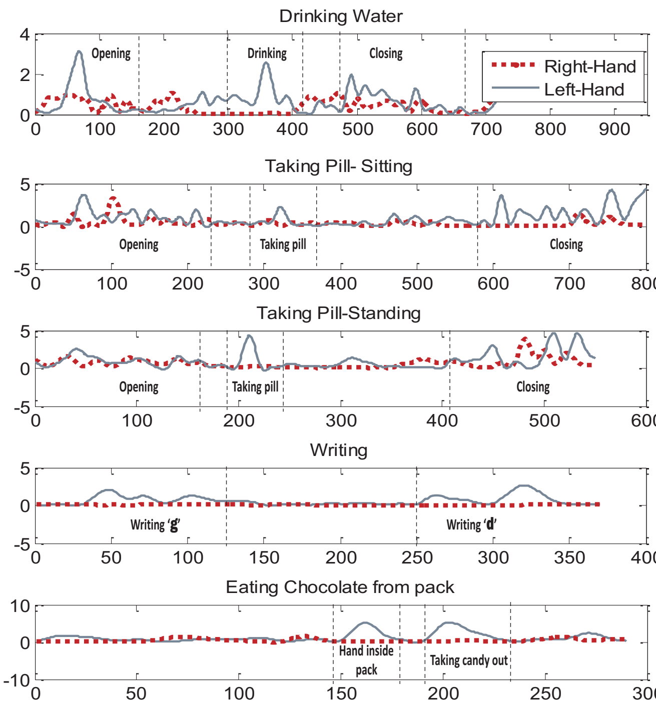



**Fig. 3:** One trial of each action scenario for both wrists.

branch on the tree. The algorithm begins with the original set of features, $FS$. During each phase, it iterates through each unused feature in $FS$ and computes the information gain for that feature. It then selects the feature with largest information gain value.

*5) Real-Time Execution:* For real-time execution of the medication adherence monitoring algorithm, the signals captured from a single sensor go through an automatic segmentation (i.e., sliding window) algorithm followed by feature extraction and motion classification. Only features that are identified as prominent during classifier training are computed for real-time execution of the algorithm.

## IV. Experimental Results

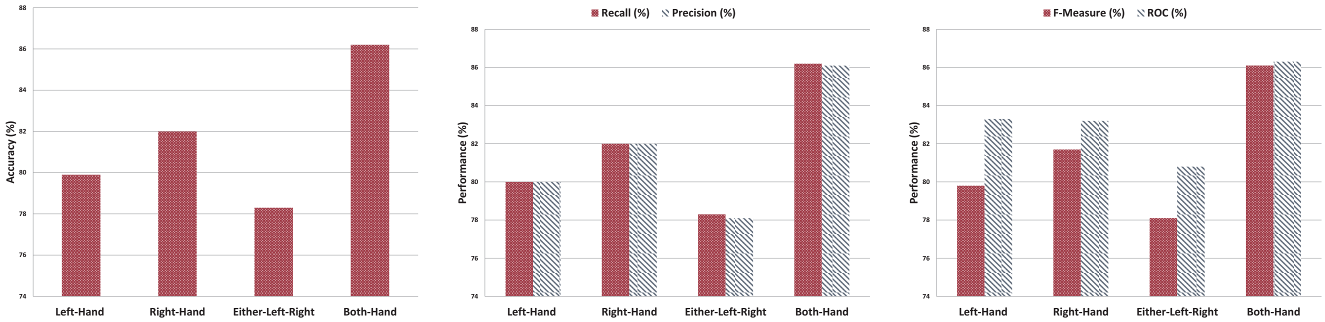
In this section, we assess the accuracy of our medication intake classifier using the collected experimental data. For designing the supervised learning based classifier, we used Weka 3.6. As described previously, before performing the analysis, the collected data are divided into five scenarios for both watches. We developed a binary classifier where one class represents medication taking scenarios and the other class is associated with the rest of the activity scenarios. According to this classification rule, scenarios 2 and 3 are labeled as *'taken'* (i.e., the action of taking a pill) and the rest of the scenarios as *'not-taken'* (i.e., an action other than taking a pill).

For comparison purposes, the classification accuracy under four different settings is investigated: (1) Combination of data from both watches (two nodes); (2) Data from the node on the right wrist; (3) Data from the node on the left wrist; (4) Data from the sensor either on the left wrist or on the right wrist (one node). In the first setting, each row of the training data contains 96 features, 48 for right hand and 48 for left hand. In this setting, prediction depends on both hands. In the second setting, only data from 'right' wrist is used; therefore, each row in the training dataset contains 48 features. The third setting is the same as the second one, except that the data from 'left' wrist is used. In the fourth setting, the classification is carried out regardless of the node's location (the smartwatch is worn either on the right wrist or on the left wrist). In other words, the data from left wrist and those of right wrist are treated the same.

We used 10-fold cross validation as our validation method. Fig 4 shows the accuracy results acquired using each setting. The confusion matrices for different settings are shown in Table II. Performance parameters presented in these graphs have the following definitions: *Precision (P)* refers to proportion of instances which truly belong to a class to the total number of instances classified as that class; *Recall (R)* represents proportion of truly classified instances divided by the total number of instances; *F-Measure* is a combined measurement of precision and recall which indicates robustness of the classifier and is given by

$$F\_Measure = 2 \times \frac{P \times R}{P + R} \quad (1)$$

Finally, *AUC* refers to the area under Receiver Operating Characteristic (ROC) curve; the closer it is to 1, the better the




(a) (b) (c)

**Fig. 4:** Classifier performance with different sensor settings (i.e., with 'left-wrist', 'right-wrist', 'both-wrists', 'either-wrists') in terms of accuracy (a), precision and recall (b), f-measure and area under curve (c).

**TABLE II:** Confusion Matrix for different settings

| Not-Taken | Taken | ←Classified As |
|---|---|---|
| 83% | 17% | **Not-Taken** |
| 24% | 76% | **Taken** |

**(a)** Error w/ Left-Hand-Only is 20.5%

| Not-Taken | Taken | ←Classified As |
|---|---|---|
| 89% | 11% | **Not-Taken** |
| 28% | 72% | **Taken** |

**(b)** Error w/ Right-Hand-Only is 19.5%

| Not-Taken | Taken | ←Classified As |
|---|---|---|
| 84.5% | 15.5% | **Not-Taken** |
| 29% | 71% | **Taken** |

**(c)** Error w/ Either-Left-Right is 22.3%

| Not-Taken | Taken | ←Classified As |
|---|---|---|
| 89% | 11% | **Not-Taken** |
| 29% | 71% | **Taken** |

**(d)** Error w/ Both-Hand is 20.0%

classifier is.

## V. Conclusion and Future Direction

In this paper, a supervised learning based methodology was proposed to monitor medication adherence using wearable sensors. Medication non-adherence has irrevocable impacts on patients and healthcare system. Our goal was to develop a system that detects medication adherence. We presented an approach to train a machine learning classifier for motion detection and adherence inference. The proposed supervised learning based methodology monitors patient's activity and recognizes the action of pill-taking. Given that motions of right and left wrists vary significantly across end-users, we developed our algorithm such that it can detect medication intake regardless of the on-body location of the wrist-band watch. Our experimental results demonstrated that with only one watch we can detect medication adherence with 78.3% accuracy.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