

Application of AI Techniques for Misuse Detection Using a Digital Motion Monitoring Module for Dry Powder Inhalers

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Summary

Inhaled therapy by dry powder inhalation has been one of the most popular routes to treat lung diseases. However, suboptimal inhaler uses, such as incorrect holding gestures, have been reported as one of key concerns affecting therapeutic outcomes. As a feasible strategy, digital dry powder inhalers (DPIs) with integrated motion monitoring system have been proposed. Facilitated by artificial intelligence (AI) technologies, the system is expected to achieve providing inhaler use error (improper positioning) information. In this study, we successfully designed a novel DPI digital motion-based monitoring system and employed widely used AI techniques to detect misuse scenarios captured from participants during inhalation. Five different AI models were evaluated, with the Extremely Randomized Trees (ExtraTrees) classifier, an ensemble learning algorithm that constructs multiple decision trees with randomized feature splits to reduce variance and enhance generalization, achieving the highest average cross-validation accuracy (0.9625) and the best test accuracy (0.9667), demonstrating strong generalization and robustness in classifying inhalation-related activities. Our findings demonstrate that AI techniques can be effectively applied to misuse detection with high accuracy, offering a promising solution to enhance the efficacy of inhaled therapy.

Key Message

A novel IMU-based digital monitoring system attached on the Breezhaler® was successfully designed with minimal impact on functionality of the inhaler. By using the selected AI techniques, the monitoring system could achieve accurate classification of different inhaler orientation-related use activities and is expected to recognize improper inhaler positioning during use.

Introduction

Respiratory diseases such as asthma and chronic obstructive pulmonary disease (COPD) are one of the most prevalent diseases, affecting a large number of populations in the whole world. Dry powder inhalation therapy has been one of the most popular routes to treat lung diseases. The delivery system is a combination of inhalable formulation and inhaler device. The effective treatment of dry powder inhalation highly relies on proper inhaler-use techniques. It has been reported that misuse errors could reach up to 80%, which greatly limits the effective delivery of medicines.

Of the reported misuses, inhaler positioning error, such as tilting and incorrect handling, is commonly seen. An *in-vitro* study by Kondo et al. investigated the impact of inhaler orientation on drug release from DPIs, and concluded that tilting the device could affect drug delivery, with the extent of the effect varying based on tilting angle and inhaler type [1]. This highlights the importance of correct DPI orientation in ensuring effective pulmonary drug delivery and achieving desired therapeutic results.

To address the use errors, digital monitoring has been one of the most promising strategies. Most currently available digital monitoring system for DPI use is pressure-based and acoustic-based. However, they could hardly provide inhaler use information on improper positioning. Therefore, it is imperative to develop a feasible and reliable system that could detect inhaler positioning error and provide real-time feedback on the errors.

IMU (inertial measurement unit) monitoring is one that could record real-time inhaler attitudes, and is reported to have applications across engineering and medical areas for motion detection, orientation tracking, and real-time feedback [2,3]. It is expected that the IMU system can also be applied to the field of inhaled therapy, to help measure the movements during DPI use and remind incorrect positioning. Currently, the related research on IMU-based digital monitoring for inhaler use is quite limited. Takano et al. developed a digital IMU-based system for Ellipta® by measuring 3-axis acceleration and 3-axis angular velocity and proved its feasibility of real-time recording of inhaler use [4]. However, manual recognition of collected IMU data poses burdens on healthcare givers and necessity the importance of automated analysis.

Herein, we developed an IMU (inertial measurement unit)-based digital monitoring system by recording inhaler motion data. More importantly, AI techniques were applied to transform the collected raw signals into interpretable inhaler use information. We hypothesized that the innovative digital module by utilizing machine learning methods could achieve inhaler use monitoring and provide inhaler orientation information, ultimately enhancing the management of respiratory diseases.

Methods and Materials

Device design. A capsule-based inhaler, Breezhaler®, was used as a model inhaler. A custom-designed, detachable digital monitoring module was integrated with the inhaler to enable motion sensing during inhalation. The module consists of a mechanical housing and embedded electronic components. As shown in Figure 1, the 3D-rendered views illustrate the structural integration of the inhaler and the monitoring module. The core sensing component is an inertial measurement unit (IMU), which provides real-time data by capturing triaxial acceleration, angular velocity, and magnetic field strength, which together describe the inhaler's spatial orientation and motion dynamics. These signals enable detection of improper misuse activities, such as incorrect inhaler holding position or shaking during inhalation.

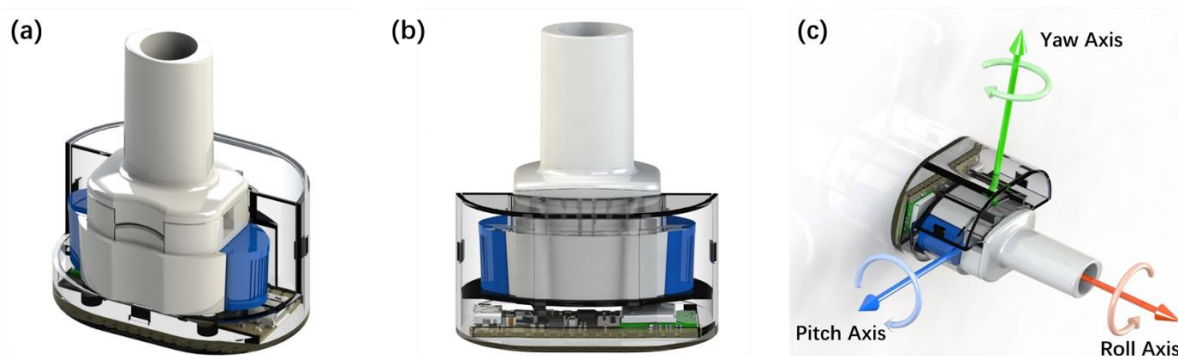


Figure 1 - The 3D views of the Breezhaler® with a custom-designed added-on digital module: (a) Trimetric view; (b) Slightly tilted front view; (c) View with reference frame indicating roll, pitch, and yaw axes

Data collection. Five types of inhaler-related activities were recorded to capture both proper usage patterns and common misuse scenarios. These included one correct use condition and four incorrect conditions: (1) correct use; (2) incorrect use – improper holding position; (3) incorrect use – capsule not pierced; (4) incorrect use – shaking detected; and (5) warning – cough detected. All data were collected in a controlled, medication-free environment to ensure participant safety. Three healthy volunteers, with informed consent, performed 20 trials per activity, yielding 60 samples per class and a total of 300 labelled samples. Each sample contained 16 signal channels, including raw IMU data and derived orientation parameters. Additionally, each scenario was performed by participants following predefined instructions, ensuring that characteristic IMU signal patterns corresponding to each use or misuse type were accurately captured and labeled. For example, an “improper holding position” was identified from orientation angles that deviated significantly from the normal upright alignment, with the pitch outside the 0–30° threshold during inhalation, typically resulting from excessive head tilting downward or upward.

Algorithms. A range of widely used machine learning algorithms were employed to classify inhaler usage behaviors, including Adaptive Boosting (AdaBoost), Extremely Randomized Trees (ExtraTrees), Support Vector Classifier (SVC), Extreme Gradient Boosting (XGBClassifier), and Logistic Regression. For each of the 16 signal channels, a comprehensive set of time- and frequency-domain features was extracted. These features covered a variety of statistical and signal characteristics, including measures of central tendency, dispersion, shape, signal complexity, extreme values, and spectral properties. Feature selection was performed using the Boruta algorithm to retain the most relevant and non-redundant features for classification [5]. Model performance was evaluated using 5-fold cross-validation and a hold-out test set (80/20 split) to ensure robustness. Cross-validation was first used to assess the generalization ability of each model across multiple data splits, and hyperparameters were optimized within this framework based on average classification accuracy. The final model was then evaluated on an independent test set to estimate performance on unseen data.

Performance measures. In this study, classification performance was evaluated using accuracy, as defined in equation (1), along with the confusion matrix. These metrics were used to compare the effectiveness of different machine learning models in distinguishing between classes.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \quad (1)$$

Results and Discussion

Classification Accuracy Analysis. The classification performance of five machine learning algorithms was evaluated using both cross-validation and independent test sets. Among all models, the ExtraTrees classifier achieved the highest average cross-validation accuracy (0.9625) and the best test accuracy (0.9667), indicating strong generalization and robustness. In comparison, SVC (0.9458), Logistic Regression (0.9417) and XGBClassifier (0.9333) showed relatively similar cross-validation performance, all maintaining high levels of accuracy. These three models also performed well on the test set, with SVC and XGBClassifier each achieving a test accuracy of 0.9500, while Logistic Regression obtained a slightly lower but still competitive accuracy of 0.9333.

In contrast, AdaBoost underperformed across both evaluation metrics, with a cross-validation accuracy of 0.7875 and a test accuracy of 0.8833. Its weaker performance may stem from its susceptibility to noisy and limited capacity to distinguish between subtly different motion patterns, particularly in cases where improper inhaler usage closely mimics correct use. Overall, these results suggest that ensemble-based models, especially ExtraTrees and XGBClassifier, are well-suited for this multi-class, motion-based classification task, likely due to their ability to capture complex, non-linear relationships within the data.

Confusion Matrix Interpretation. Figure 2 presents the normalized confusion matrices for each classifier, providing deeper insight into class-wise performance across the five activity categories. The ExtraTrees classifier achieved 100% accuracy for all classes except Class 2 (Wrong holding position, 88%), demonstrating its strong robustness and reliability in distinguishing between variations in inhalation activities.

Both SVC and XGBClassifier also demonstrated high discriminative performance. SVC correctly identified Class 1 (correct use) with 91% accuracy, while misclassifying 9% of Class 1 instances as Class 5 (cough). It also showed 6% confusion between Classes 3 and 4. Similarly, XGBClassifier classified Class 1 with 91% accuracy, but 9% of those instances were again misclassified as Class 5. Class 2 (wrong holding position) was predicted with 94% accuracy by both SVC and XGBClassifier. Logistic Regression showed slightly higher confusion between Class 1 and Class 2, correctly identifying Class 1 with 82% accuracy, while 12% of Class 2 instances were misclassified as Class 1. Nonetheless, Classes 3 (capsule not pierced), 4 (device shaken), and 5 (cough) were identified with 100% accuracy.

In contrast, AdaBoost exhibited relatively notable misclassification, with only 55% accuracy on Class 1. It misclassified 9% of Class 1 instances as Class 2 and 18% each as Classes 4 and 5. This confusion strongly affected its overall performance and suggests insufficient ability to distinguish differences in usage behavior.

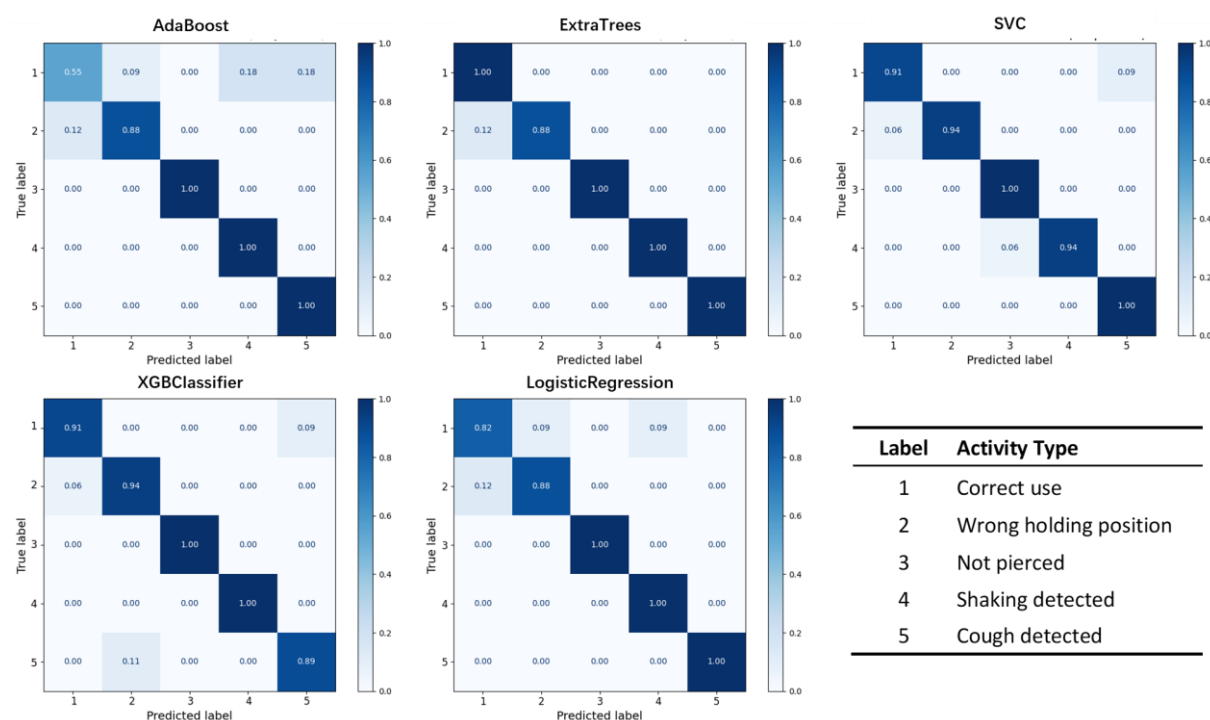


Figure 2 - Normalized confusion matrices for the five classifiers on the test set

Limitations and Future Work. Despite the promising results, this study has several limitations. The small sample size limits model generalizability, underscoring the need for larger and more diverse datasets. Although the digital module was carefully designed to minimize interference with airflow and drug delivery, full design details cannot be disclosed due to space and patent constraints. Future work will focus on expanding the dataset, incorporating real-world usage scenarios, and deploying lightweight AI models on embedded systems for real-time inhaler monitoring. The models developed in this study, particularly tree-based classifiers such as ExtraTrees, have relatively low computational complexity and are suitable for implementation on embedded platforms.

Conclusions

In conclusion, a novel digital motion-based monitoring system was successfully developed and integrated with the inhaler. By using various AI techniques, the accurate classification of inhalation orientation related activities was achieved. The system proves the feasibility of AI-empowered IMU-based system in providing inhaler orientation information, and is expected to achieve improved inhaler techniques and therapeutic results of inhaled therapy. The intended end-users of this system include both patients, who can receive real-time feedback to correct improper handling, and healthcare professionals, who can use the collected data to assess adherence and optimize inhalation training.

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