A Preliminary Study of Hand Hygiene Compliance Characteristics with Machine Learning Methods

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***Abstract*— Increasing hospital re-admission rates due to Hospital Acquired Infections (HAIs) are a concern at many healthcare facilities. To prevent the spread of HAIs, caregivers are expected to comply with recommended hand hygiene guidelines, which require reliable and timely hand hygiene compliance measurement systems. The current standard practice of monitoring compliance involves the direct observation of caregivers' hand cleaning as they enter or exit a patient room by a trained observer, which can be time-consuming, resource-intensive, and subject to bias.**

To alleviate the heavy manual effort and reduce errors, this paper studies the characteristics of compliance that could be used to assist the direct observation approach by deciding when and where to station manual auditors and to improve compliance by providing just-in-time alerts or potentially recommending training materials to non-compliant staff.

The paper analyzes location and handwashing station activation data from a 30-bed intensive care unit (ICU) and uses machine learning to assess if location, time-based factors, or other data can be used to predict handwashing non-compliance events. The results show that a care provider's entry compliance is highly indicative of the same provider's exit compliance and that compliance of the most recent patient room visit can also predict entry compliance of a staff member's current patient room visit

I. INTRODUCTION

Concerns about Hospital Acquired Infections (HAIs) have emerged in recent years due to increasing hospital re-admission rates. Hospital caregivers are often blamed for patient re-admissions arising from continual exposure to bacteria and diseases. In particular, without good sanitary practices, contaminated hands can become major carriers of infections that are often transmitted to patients through physical contact.

To prevent the spread of HAIs in healthcare facilities and reduce re-admission rates, healthcare professionals are expected to comply with recommended hand hygiene guidelines. The current standard practice for compliance monitoring employs human auditors to directly observe and record hand hygiene compliance of medical workers unobstrusively, which is both resource-intensive and subject to bias [1] (*e.g.*, evidence of the Hawthorne effect [2]). An alternative approach is to use a real-time location system and smart dispensers to monitor handwashing compliance by tracking provider location and activation of dispensers.

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This paper analyzes two months of real-time location data and handwashing dispenser data for the care providers in a 30-bed intensive care unit (ICU). The goal of this study was to use machine learning to assess if there are location, time-based, or other behavioral characteristics that can be used to predict handwashing non-compliance events in advance. For example, having observed a provider with a non-compliant room entry, we attempt to predict if the same provider will also be non-compliant when exiting the room. Using possible correlating factors to handwashing, we should be able to predict at least one handwashing action ahead of time. We can then use this information to assist the direct observation approach by deciding when and where to station manual auditors and to improve compliance by providing just-in-time alerts or potentially recommending training materials to predicted non-compliant staff.

The remainder of this paper is organized as follows: Section II presents five hypotheses regarding compliance characteristics investigated in our research; Section III describes the data collection instrumentation setup; Section IV evaluates the hypotheses with machine learning predictions and analyses of the preliminary classification results; Section V presents concluding remarks and outlines future extensions of our work.

II. HYPOTHESES

This section poses five hypotheses to help identify characteristics of handwashing compliance and its predictability. *Entry/Exit compliance* is defined as hand hygiene compliance observed at each caregiver's entry or exit to a patient room, determined by *wash on entry/exit*. To predict compliance, therefore, we need to perform a binary classification of handwashing actions using features of the movement and handwashing history of a provider. The following postulates how we build these handwashing classifiers based on different features of a provider's movements and handwashing compliance history.

Hypothesis 1: Handwashing on room entry is indicative of washing on exit. Most human auditing approaches focus on auditing handwashing behavior that is observed outside of a patient room, which may only show an entry or exit wash (*e.g.*, a provider may wash their hands inside of the room on entry and outside of the room on exit). An important question, therefore, is how predictive observing one of the washing events is in predicting the other (*e.g.*, if a human auditor only sees a wash on exit, what does this tell us about wash on entry?). Our hypothesis is that handwashing on room entry is indicative of washing on exit. Handwashing can be a habitual—and thus predictable—behavior for hospital caregivers, depending on how well they abide by hand hygiene guidelines.

Hypothesis 2: Time-related features may be indicative of handwashing. For instance, compliance may decrease when patients are asleep between midnight and 5am due to two likely reasons: (1) care providers have limited physical contact with patients hence less need to sanitize or 2) reduced Hawthorne effect since patients are not awake to observe their hand hygiene compliance.

Hypothesis 3: Location may affect handwashing behavior. We hypothesize that caregivers' compliance may be affected by which patient room they visit. The study in [2] recognizes the Hawthrone effect with the standard direct compliance observation approach. Likewise, care providers may perform better sanitation under observation when visiting locations that are clearly in view of other staff members or supervisors, such as rooms closest to nurse's stations.

Hypothesis 4: Staff's recent wash in/out behavior affect entry/exit compliance. We speculate that if previously visited patients were infectious, then it is highly likely that the staff would wash their hands more frequently. Conversely, if these patients were *not* infectious, they may feel there is less need for hand hygiene. Previous handwashing behavior could may therefore indicate current compliance.

Hypothesis 5: There may be other features that are possibly predictive of compliance. We suspect that the features selected based on our intuition may have excluded other correlating factors of compliance. To find other possible predictors, therefore, we can use feature selection, which is the process of selecting the most relevant subset of predictors for constructing classifiers.

III. INSTRUMENTATION SETUP

The dataset was provided by ZH Solutions (which is a smart beacon technology and data anlystics company) and covered two months of data from 30 patient rooms in an ICU. The location data was produced from a Bluetooth Low Energy indoor positioning system that provides room-level accuracy for reporting staff locations in real-time. All staff members were required to wear a Bluetooth Low-Energy badge.

Likewise, all staff were required to sanitize their hands within a short interval (2 minutes) of entering a patient room and before exiting the same room. Each compliant patient room visit should have been associated with an activation of a specific soap dispenser with disinfectant solution against Clostridium difficile [3]. These dispensers are located both inside and outside each patient room.

The ICU deployed active monitoring handwashing stations that recorded each activation. These activation events were combined with real-time location data to track individual staff handwashing compliance. On entry to a room, the system expected to see at least one handwashing event from a station inside of the room within two minutes or from the handwashing station immediately outside the room prior to entry.

	Class: *Washed on Entry*				Class: *Washed on Exit*			
Classifier	Accuracy	Recall	F-Score	AUC	Accuracy	Recall	F-Score	AUC
RF	89.20%	0.892	0.893	0.927	88.83%	0.888	0.889	0.922
SMO	89.35%	0.893	0.894	0.878	89.35%	0.893	0.893	0.869
NB	82.25%	0.822	0.829	0.907	79.88%	0.799	0.806	0.898
FFNN	90.00%	0.878	0.877	0.869	88.80%	0.875	0.866	0.86
RNN	91.20%	0.908	0.901	0.9	88.40%	0.864	0.862	0.853

Fig. 1. Entry and Exit Compliance Classification Results Using All Features in the Dataset

IV. HYPOTHESES EVALUATION

After restructuring and sanitizing the data collected, we obtained a dataset with 17 features, where two are the class variables of interest (*i.e.*, *wash on entry* and *wash on exit*). We then split the data to a 75% classifier training set and a 25% test set for assessing the classification performance. We employed the following machine learning classification algorithms from the Weka [4] and Deeplearning4J (DL4J) [5] libraries:

1) Random Forest (RF) with 1 random seed and 100 iterations
2) Sequential Minimal Optimization (SMO) implementation of the Support Vector Machine (SVM) with default parameters
3) Naive Bayes (NB) with Weka's default parameters
4) Feed-Forward Neural Network (FFNN) with 3 layers, 6 random seed, 1000 iterations, a 0.1 learning rate, and Stochastic gradient descent optimization [6]
5) Recurrent Neural Network (RNN) with 3 layers, two of which are Graves' Long Short-Term Memory (LSTM) layers [7] as the input and hidden layers, and the same parameters as the FFNN.

Training models with all features. As a first step examined how well handwashing can be predicted at least one step in advance (*e.g.*, if a care provider washed in on entry to a patient room, can we predict their wash out behavior). To do so, we trained the machine learning models with all the features in the dataset. The classification results are shown in Fig. 1 with a consistently high accuracy at 80+% and high other metrics above 0.8. These results indicate that some factors can be predictive of compliance. To identify the specifics, we therefore conducted the following experiments to evaluate the hypotheses described in Section II.

A. *Evaluating Hypothesis 1: Handwashing on room entry is indicative of washing on exit.*

Experiment setup. We prepared two datasets for each class variable with one set including the counterpart class variable (*i.e.*, dataset with 16 features) and the other excluding it (*i.e.*, data with 15 features). To obtain the second set of training and test data, we applied an unsupervised remove attribute filter from the Weka library to remove the class variable not being predicted.

	Class: *Washed on Entry*				Class: *Washed on Exit*			
Classifier	Accuracy	Recall	F-Score	AUC	Accuracy	Recall	F-Score	AUC
RF	69.08%	0.691	0.704	0.743	67.75%	0.678	0.689	0.709
SMO	75.74%	0.757	0.759	0.713	74.56%	0.746	0.746	0.7
NB	69.38%	0.694	0.707	0.794	68.42%	0.684	0.697	0.786
FFNN	79.20%	0.708	0.72	0.789	78.40%	0.734	0.73	0.699
RNN	76.80%	0.721	0.713	0.782	76.00%	0.7	0.71	0.722

Fig. 2. Compliance Prediction Results excluding the Counterpart Class Variable.

	Class: *Washed on Entry*				Class: *Washed on Exit*			
Classifier	Accuracy	Recall	F-Score	AUC	Accuracy	Recall	F-Score	AUC
RF	61.46%	0.615	0.616	0.539	59.76%	0.598	0.597	0.524
SMO	70.64%	0.706	0.585	0.5	69.45%	0.695	0.569	0.5
NB	66.12%	0.661	0.639	0.572	64.79%	0.648	0.631	0.587
FFNN	70.80%	0.552	0.583	0.563	68.40%	0.532	0.559	0.52
RNN	72.00%	0.542	0.574	0.551	70.00%	0.54	0.577	0.523

Fig. 3. Compliance Classification Results Based on Time-related Features.

Results. Fig. 1 shows the classification results produced using the dataset with 16 features, with a consistently high accuracy from each classifier at an average of 89% for *wash on entry* and 87% for *wash on exit*. Results in Fig. 2 correspond to the dataset with 15 features with an average *wash on entry* prediction accuracy of 75% and *wash on exit* of 73.5%.

Analysis of results. The overall classification accuracy of *wash on entry* is much higher when its counterpart, *wash on exit*, is taken into account and vice versa, meaning that *wash on entry* is highly predictive of *wash on exit*. With a provider's entry compliance, therefore, if they are predicted non-compliant on room exit, we can provide a hand hygiene reminder to the provider.

B. Evaluating Hypothesis 2: Time-related features may be indicative of handwashing.

Experiment setup. For this study, we applied Weka's remove attribute filter to remove all non-time related features from the dataset and use the generated new dataset with the classifiers.

Results. The results shown in Fig. 3 have 60+% accuracy in most cases for both class variables. Specifically, deep nets and SMO models achieved prediction accuracies around 71% for *wash on entry* and 69% for *wash on exit*.

Analysis of results. A closer analysis of the classification result metrics indicate that despite the classification accuracy being acceptable, the AUC (a valuable metric for evaluating classification) is around 0.5, meaning that the results are no better than random guesses. This result indicates that time factors have little impact on determining handwashing and cannot be used to forecast handwashing.

	Class: *Washed on Entry*				Class: *Washed on Exit*			
Classifier	Accuracy	Recall	F-Score	AUC	Accuracy	Recall	F-Score	AUC
RF	68.57%	0.686	0.699	0.746	68.71%	0.687	0.699	0.733
SMO	65.16%	0.652	0.665	0.717	65.01%	0.65	0.662	0.709
NB	65.90%	0.659	0.673	0.707	65.75%	0.658	0.67	0.704
FFNN	75.20%	0.591	0.669	0.723	74.80%	0.55	0.601	0.642
RNN	74.80%	0.569	0.653	0.71	71.60%	0.576	0.625	0.65

Fig. 4. Compliance Classification Results Based on Location-related Features.

C. Evaluating Hypothesis 3: Location may affect handwashing behavior.

Experiment setup. Similar to the setup when evaluating Hypothesis 2, we altered the original dataset using Weka's remove attribute filter to exclude data unrelated to location information.

Results. The results shown in Fig. 4 have accuracies above 65% in all cases for both class variables. In particular, deep net models achieved an average prediction accuracy of 75% for **wash on entry** and 73% for **wash on exit**.

Analysis of tesults. The classification results output by the deep net models are more optimistic and consistent with medium accuracy. We therefore infer thatlocation, unlike time-related factors, has more of an impact on predicting handwashing on entry and exit, although not as indicative as the class variables of each other.

D. Evaluating Hypothesis 4: Staff's recent wash in/out behavior affect entry/exit compliance.

Experiment setup. To include the previous wash in/out event, we sorted the dataset by staff ID and then timestamp. For each data entry we then added the immediate previous wash on entry/exit associated with the same staff and discarded all entries without any previous data.

Results. The classification results are shown in Fig. 5. Most classifiers achieved an 74+% accuracy for both class variables.

Analysis of results. Most classifiers produced consistently optimistic prediction results of the two class variables, and all performance metrics are above a confident value of 0.7. This result suggests that a provider's most recent handwashing behavior can be useful for predicting wash on entry/exit of the next visit.

E. Evaluating Hypothesis 5: There may be other features that are possibly predictive of compliance.

Experiment setup. In this experiment we ran Weka's attribute selection tool with three selection evaluators with corresponding search methods, namely (1) CfsSubsetEval with GreedySetpwise, (2) InfoGainAttributeEval with Ranker, and (3) WrapperSubsetEval with GeneticSearch. The goal was to find the union in the produced feature lists and then eliminate all other features to generate the most relevant feature subsets.

	Class: *Washed on Entry*				Class: *Washed on Exit*			
Classifier	Accuracy	Recall	F-Score	AUC	Accuracy	Recall	F-Score	AUC
RF	64.05%	0.641	0.655	0.692	63.54%	0.635	0.648	0.682
SMO	75.74%	0.757	0.759	0.713	74.56%	0.746	0.746	0.7
NB	75.07%	0.751	0.753	0.795	74.04%	0.74	0.742	0.784
FFNN	77.60%	0.721	0.715	0.781	77.20%	0.706	0.72	0.763
RNN	77.20%	0.729	0.734	0.774	78.80%	0.732	0.729	0.78

Fig. 5. Predictions of Compliance Using Previous Handwashing Data

	Class: *Washed on Entry*				Class: *Washed on Exit*			
Classifier	Accuracy	Recall	F-Score	AUC	Accuracy	Recall	F-Score	AUC
RF	89.05%	0.891	0.892	0.925	89.05%	0.891	0.891	0.922
SMO	89.35%	0.893	0.894	0.878	89.35%	0.893	0.893	0.869
NB	82.25%	0.822	0.829	0.907	79.88%	0.799	0.806	0.898
FFNN	90.00%	0.878	0.877	0.869	88.80%	0.875	0.866	0.86
RNN	91.20%	0.908	0.901	0.9	88.40%	0.864	0.862	0.853

Fig. 6. Compliance Predicted with Automatically Selected Features

Results. The features selected for class *wash on entry* are *wash on exit*, *previous wash on exit*, and *location x coordinate*, and *wash on entry* for class *wash on exit*. The classification results are shown in Fig. 6 outputting an average accuracy of 88.5% and 87% for both classes.

Analysis of results. The results validated our previous observations made in Research Questions 1, 2, 4 for *wash on entry* with a specific location factor being *location x coordinate* and Question 1 for *wash on exit*. They also indicate that no other feature can characterize handwashing or hand hygiene compliance.

F. Threats to Validity

The main threat to validity of our work is that we based our findings upon assumptions made about the data. We performed analyses on the data assuming that the staff were using their badges at all time, but in fact, some of them were sporadically observed without badges. To minimize the impact of this behavior in our findings, we used location data to filter out dispenser events not associated with nearby caregivers, keeping all dispenser events that were associated with badged staff.

Unfortunately, there is still the possibility that a staff member without a badge activated the dispenser while staying in the same room with another badged staff, making the system wrongly assign the event to the staff wearing the badge. In our analysis of the data, however, we found it was uncommon for two caregivers to remain in the same room at the same time. We therefore believe these cases would only marginally skew our findings.

Finally, we did not count hallway hand hygiene events but only those occurred in a room. This method does not change the nature of our findings, however, as we care mostly about compliance related to patient room visits.

V. CONCLUDING REMARKS

This paper analyzed location and handwashing station activation data from a 30-bed ICU and assessed the factors that are predictive of compliance. We posed a number of hypotheses regarding the potential predictors and provided evaluations by conducting experiments using different sets of data against our machine learning models. We observed that a care provider's entry compliance is highly indicative of their exit compliance and that compliance of the most recent patient room visit can also predict entry compliance of a staff member's current patient room visit.

Existing research studies in [8] [9] [10] [11] and [12] focus on using electronic compliance monitoring systems to increase hand hygiene performance by providing real-time feedback to the care providers. Little or no previous literature, however, has attempted to predict compliance using machine learning techniques. Our study is therefore unique in the sense that it uses the collected data to *predict* the next future compliance behavior ahead of time to proactively avoid non-compliance, while other approaches *react* to non-compliance.

In future work we plan to use more compliance data as it becomes available to further verify our current observations. With predictive features of compliance, we can then integrate our prediction models to the system. Our goal will be to assist the direct observation approach by deciding when and where to station manual auditors and to improve compliance by providing just-in-time alerts or potentially recommending training materials to predicted non-compliant staff.

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