Applying Machine Learning Methods to Predict Hand Hygiene Compliance Characteristics

Peng Zhang[1], Jules White[1], Douglas Schmidt[1], and Tom Dennis[2]

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 should comply with hand hygiene guidelines, which require reliable and timely hand hygiene compliance monitoring 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 tedious manual effort and reduce errors, this paper describes how we applied machine learning to study the characteristics of compliance that can later be used to (1) assist direct observation by deciding when and where to station manual auditors and (2) improve compliance by providing just-in-time alerts or recommending training materials to non-compliant staff.**

The paper analyzes location and handwashing station activation data from a 30-bed intensive care unit study and uses machine learning to assess if location, time-based factors, or other behavior data can determine what characteristics are predictive of handwashing non-compliance events. The results of this study show that a care provider's entry compliance is highly indicative of the same provider's exit compliance. Moreover, compliance of the most recent patient room visit can also predict entry compliance of a provider's current patient room visit.

I. INTRODUCTION

Hospital Acquired Infections (HAIs) are a common cause of 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, as well as to 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 that directly observe and record hand hygiene compliance of caregivers unobtrusively, which is resource-intensive and subject to bias [1] (*e.g.*, evidence of the Hawthorne effect [2], the process where human subjects of an experiment alter their behavior due to their awareness of being studied.) 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.

[1]Institute for Software Integrated Systems, Vanderbilt University, Nashville, TN, USA. Professor Jules White is an equity holder in Ziiio, Inc., which aided in the production of the location data {peng.zhang, jules.white, d.schmidt}@vanderbilt.edu

[2]ZH Solutions, Nashville, TN, USA tdennis@zhs.io

This paper analyzes two months of real-time location data and handwashing dispenser activation events for the care providers in a 30-bed intensive care unit (ICU). The goal of this study is to use machine learning to assess if there are location, time-based, or other behavioral characteristics that predict handwashing non-compliance events in advance. For example, having observed a provider with a non-compliant room entry, we can predict if the same provider will also be non-compliant when exiting the room. Using possible correlating factors to handwashing, we can predict at least one handwashing action ahead of time. This information can be applied to (1) assist the direct observation approach by deciding when and where to station manual auditors and (2) 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 poses five hypotheses regarding compliance characteristics we investigated; 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 work.

II. SUMMARY OF HYPOTHESES

This section poses five hypotheses that help identify key characteristics and predictablity of handwashing compliance. *Entry/Exit compliance* is hand hygiene compliance observed at each caregiver's entry or exit to a patient room, determined by *wash on entry/exit*. To predict compliance we perform a binary classification of handwashing actions using features of the movement and handwashing history of a provider. Below we postulate how to evaluate these handwashing classifiers based on different features of a provider's movements and compliance history.

Hypothesis 1: Handwashing on room entry is indicative of washing on exit. Most auditing approaches evaluate handwashing behavior observed outside of a patient room, which may only show an entry or exit wash (*e.g.*, a provider may wash their hands inside the room on entry and outside the room on exit). An important question 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?). We hypothesize that handwashing on entry is indicative of washing on exit. Handwashing can be a habitual—and thus predictable—behavior for hospital caregivers, depending on whether they abide by hand hygiene guidelines.

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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 these likely reasons: (1) care providers have limited physical contact with patients, hence less need to sanitize, (2) to reduce noise from activating the dispensers that may disturb patients, and (3) reduced Hawthorne effect since patients are not awake to observe 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 or supervisors, such as rooms closest to the nurses' stations.

Hypothesis 4: Staff's recent wash in/out behavior may 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 may therefore indicate current compliance.

Hypothesis 5: There may be other features that are possibly predictive of compliance. We postulate that the features selected based on our intuition may have excluded other correlating factors of compliance. To find other possible predictors, we therefore 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 analytics company) and covered two months of data from 30 patient rooms in an ICU. The location data was produced from a Bluetooth Low Energy (BLE) indoor positioning system that provided real-time room-level accuracy for reporting staff locations. All staff members wore a BLE badge.

In addition, the ICU deployed active monitoring handwashing stations that recorded each activation of a specific soap dispenser with disinfectant solution against Clostridium difficile [3], a common and severe HAI easily spread through physical contact. These activation events were combined with real-time location data to track care providers' handwashing compliance. On entry to a room, the system expected to see at least one handwashing event from inside of the room within two minutes or from the handwashing station immediately outside the room prior to entry.

IV. Hypotheses Evaluation

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

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 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.

	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

Training models with all features. As a first step we 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). We therefore trained the ML models with all features in the dataset. The classification results are shown in Fig. 1 with a consistently high accuracy at 80%+ and other metrics above 0.8. These results indicate that some factors can be predictive of compliance. To identify the specifics, we 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.

Results. Fig. 1 shows the classification results produced using the dataset with 16 features, with a consistently high accuracy across classifiers 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*

	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.

	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.

	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

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 features unrelated to time from the dataset and fed the generated dataset to the ML 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 indicates 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 suggests that time factors have little impact on determining handwashing and cannot be used to forecast handwashing.

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 ML models achieved an average prediction accuracy of 75% for *wash on entry* and 73% for *wash on exit*.

Analysis of results. The classification results output by the deep net ML models are more optimistic and consistent with medium accuracy. We therefore infer that location, 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 may 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 produced an accuracy of 74%+ for both class variables.

Analysis of results. Most ML classifiers produced consistently optimistic prediction results of both 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/feature selection tool with three selection evaluators with corresponding search methods, namely (1) CfsSubsetEval with GreedyStepwise, (2) InfoGainAttributeEval with Ranker, and (3) WrapperSubsetEval with GeneticSearch. The

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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

goal was to find the union in the produced feature lists and then eliminate all other features to generate the most relevant feature subsets.

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 Hypotheses 1, 2, 4 of *wash on entry* with a specific location factor being *location x coordinate* and Hypothesis 1 of *wash on exit*. They also indicate that no other feature can characterize compliance behavior.

F. Threats to Validity

The main threat to validity of our work is that we based our findings upon some assumptions made about the data. For instance, we performed analyses on the data assuming that all on duty staff were using their badges at all time. In practice, however, some of staff were sporadically observed without badges. To minimize the impact of this behavior in our findings, we used location data to filter out dispenser activation events not associated with nearby caregivers, retaining all events that were associated with only badged staff.

Unfortunately, there is also the possibility that a staff member without a badge activated the handwashing station while staying in the same room with another badged staff, making the system wrongly assign the event to the staff wearing the badge. Nevertheless, in our analysis of the data, we found it was uncommon for two (or more) 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 account for hallway hand hygiene events but only those occurred in patient rooms. This method, however, does not change the nature of our findings as we care mostly about compliance related to patient room visits.

V. CONCLUDING REMARKS

This paper analyzed location data and handwashing station activation events from a 30-bed ICU and assessed the factors that are predictive of handwashing 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 (ML) classifiers. We observed that (1) a care provider's entry compliance is highly indicative of exit compliance and that (2) a provider's compliance of the most recent patient room visit can also predict entry compliance of the same provider's current patient room visit.

Existing research 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 care providers. Little or no previous literature, however, has predicted compliance using ML 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 existing compliance monitoring systems. 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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