Better Technology, Better Outcomes.

The Effects of Machine Learning Powered Remote Patient Monitoring on Home Health Care

White Paper | July 2015

wecare® HOME HEALTH SERVICES

PART OF CBI HEALTH GROUP

AlayaCare

Executive Summary

This white paper is a collaborative effort between AlayaCare, a software company for community care providers, and CBI Health Group, Canada's largest provider of rehabilitation and home health services under several brands including We Care. The paper discusses the benefits of applying machine learning to streams of incoming remote patient monitoring vitals for decision support. The vital data was provided by We Care, who analyzed/collected over three years of patient monitoring. The machine learning analysis and development was executed by AlayaCare labs – the research and development arm of AlayaCare software.

AlayaCare and We Care adhere to the philosophy that both face-to -face and virtual care (remote monitoring, video conferencing) are increasing areas of focus for payers and providers. As such, introducing new technology like Machine Learning and Big Data to bolster this trend and support clinicians in their decisions is the topic of this paper.

Our research shows that machine learning can improve event predictions by 11% while reducing over-diagnosis by 54%

Machine learning is a branch of artificial intelligence (AI) based on two areas; mathematical algorithms and automation. The idea is to automate the building of analytic models that use algorithms to "learn" from data in an iterative fashion. The "machine" (really an algorithm) learns from its mistakes in previous steps to derive the best results without human intervention. These models can then be used to produce reliable, repeatable decisions. Moreover, machine leaning in combination with 'Big Data' can deliver the following capabilities to AlayaCare partners:

- **Risk scoring, which informs and provides insight to clinicians of possible adverse events such as falls,episodes, events and hospitalization (emergency) visits.**
- **More accurate prediction of events (True Positives).**
- **Reduction of over diagnoses (False Positives).**
- **Patients can remain at home longer with machine learning.**

Our research shows that machine learning can improve event predictions by 11% while reducing over-diagnosis by 54% compared to manually set thresholds. This leads to better patient outcomes and major bottom line savings for home health care agencies.

Introduction

Canada, as many other countries, is experiencing rapid growth within its aging population. Seniors make up the fastest-growing age group, with no signs of slowing down. It is projected that by 2036 there will be roughly 9 million (1 in 4 Canadians) over the age of 65, with 85% of those seniors expected to develop chronic conditions (Ward et al. 2014). Accepting the fact that the elderly population will continue to grow and cause a steady increase in the demand for health care, it would be tactical for Canada to investigate potential restructuring of health care delivery to meet the needs of the growing senior population—the obvious alternative being home health care. CHA (Canadian Health Association) released a policy brief labeled, "Home Care in Canada: From the Margins to the Mainstream" that identified four reasons why home health care is becoming more mainstream (CHA, 2009):

1. People generally prefer to receive care at home.
2. Canada is a nation with increasing rates of chronic conditions.
3. Governments are trying to limit expenditures and home health care presents a lower cost solution.
4. Current technology allows us to deliver better home health care.

Based on the substantial volume of clinical and event data (hospital readmissions and Emergency Room visits) gathered in the health care system, and the growing popularity of home health care, AlayaCare and We Care have partnered together to produce an innovative approach to reducing adverse events—**machine learning augmented home health care**. The transformational potential of machine learning has yet to be seen in the home health care industry, but this paper aims to establish the required foundation.

Overview

Machine learning is a type of artificial intelligence that is concentrated on developing algorithms that analyze data and predict future events with tremendous accuracy. It is a technology that is well suited to identify hidden trends and patterns in vast amounts of data, not visible to the human eye.

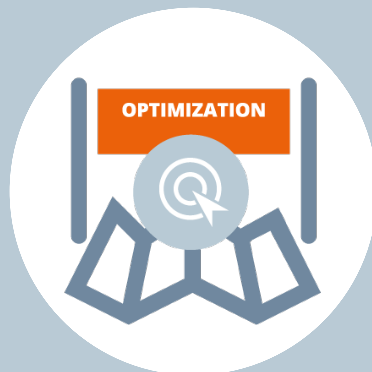
"Can machine learning algorithms, applied to remote patient monitoring data, help home health care agencies reduce the number of hospital re-admissions and Emergency Room visits?"

Machine learning algorithms have been successfully applied to a vast array of industries; from finance to retail, and even health care. It is so embedded in our everyday lives that we hardly know it is there. With AlayaCare providing data science resources, and We Care providing clinical expertise and data, this study focuses on answering the following question: can machine learning algorithms, applied to remote patient monitoring data, help home health care agencies reduce the number of hospital re-admissions and Emergency Room visits?

AlayaLabs

Taking Home Healthcare Software to the Next Level

Machine Learning to Harness your Data



Reduced Cost Through Optimization

Rich Insightful Long Term Planning

We Care Re-ACT Program

We Care Remote Access to Care Technology (Re-ACT) is a remote health monitoring program created to optimize the management and treatment of seniors who are living with chronic disease(s).

Re-ACT uses wireless technology and monitoring devices to remotely connect seniors to a Registered Nurse (RN), who can then monitor, assess, and manage their chronic condition(s) and corresponding care plans. Patients are trained to use their monitoring device daily to check vital signs, and the data is subsequently stored on a secure server where results are then populated and categorized on a risk alert scale (normal to high) for RN and physician review. The main focus of the program is to reduce unnecessary hospitalizations and Emergency Room visits while encouraging patients' individual participation and skill development for managing their chronic conditions at home (We Care, 2011).

Operating out of We Care's Monitoring Centre in Barrie, Ontario, the Re-ACT program is supported by a partnership with the NSM Community Care Access Centre (NSM CCAC) and We Care Home Health Services. The program serviced roughly two hundred and fifty-six (256) clients ages 42-97 over 9,200 square kilometers. In a three-year period, We Care reported that 80% of clients are confident that they will be able to stay at home longer than before beginning Re-ACT, while 88% reported being very satisfied with the program (We Care, 2011). The Re-ACT technology has proven to increase healthy aging at home initiatives, and overall quality of life for clients living at home with chronic conditions.

For more information on the Re-ACT program, refer to the We Care Remote Access to Care Technology white paper: http://www.wecare.ca

Methodology

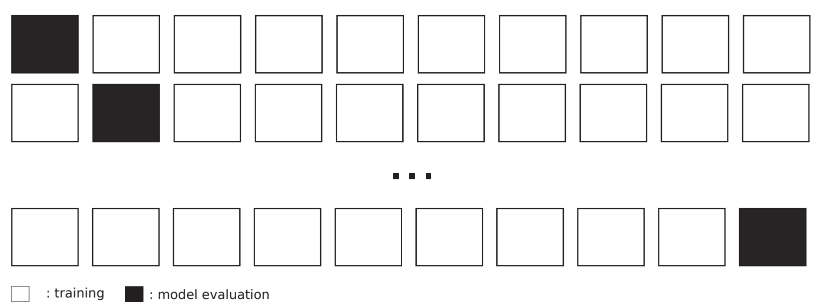
To begin answering the fundamental study question, our methodology was broken down into three steps: **Dataset Creation, Model Training, and Performance Evaluation**

1 Dataset Creation

A dataset is a collection of dated and identified observations. To measure the performance of our machine learning algorithms, the results were directly compared to a dataset compiled of observations from the We Care Re-ACT program. These observations consisted of: the patients' diagnosed conditions (COPD, CHF, etc.), the daily monitored vital signs readings (weight, blood oxygen, pulse, blood pressure, and temperature), and the different events (in this case, hospital readmissions and ER visits). For this study, the algorithm was programmed to flag events three days prior, so care workers could potentially prevent the event from happening. This means that if a hospital readmission were predicted to happen on Sunday, Thursday, Friday and Saturday would be flagged as events.

2 Model Training

Step two consisted of training an algorithm on the compiled dataset. In order to have an unbiased model performance evaluation, we used an algorithm called ten-fold cross-validation. This algorithm separates the dataset into 10 folds, using nine for training, and one to evaluate. This iterates until all folds have been used to measure performance. In order for the algorithm to train itself, it observes the dataset and eventually learns to predict when one is an example of a day leading to an event.



3 Performance Evaluation

Lastly, step three consisted of testing and evaluating how our trained algorithm performed versus manually setup alarms by care workers. To do so, we first combined predictions of all left-out folds that were compiled during training. During the Re-ACT program (which was executed without machine learning algorithm) the care worker would manually set thresholds on vital signs, which would trigger an alert when breached. Considering the care workers predicted an event when one or many alerts were flagged for a day of monitoring, we obtained a set of predictions for every example in the dataset: one from the care workers alerts and one from the trained algorithm.

Results

Model Performance

The performance measures are presented as true and false positives and negatives of events, the sensitivity, the specificity, and the sum of both measures (SMB). True and false positives and negatives are often presented as a confusion matrix (Figure 1).

Sensitivity: True Positive / (True Positive + False Negative)
Specificity: True Negative / (True Negative + False Positive)
SMB: Sensitivity + Specificity

The sensitivity and specificity are both measures derived from this confusion matrix to measure the true positive and true negative rates. In other words, the sensitivity shows the rate of days leading up to an event that the prediction captured, and the specificity shows the rate of days that didn't suspect an event that the prediction captured. The higher the value of these measures, the better. The sum of both measures represents the accuracy of the model. This measure was used because the dataset is highly imbalanced, considering the fact that events are rare. With events only happening 0.6% of the time, an accuracy of more than 99% could mean that the prediction would strictly forecast days that don't suspect an event, defeating the purpose of the study.

Figure 1 - Performance Measures

		Prediction: No	Prediction: Yes
Actual Value	No	TN: The prediction that the day was not leading to an event was correct.	FP: The prediction that the day was leading to an event was incorrect.
Actual Value	Yes	FN: The prediction that the day was not leading to an event was incorrect.	TP: The prediction that the day was leading to an event was correct.

Care workers were able to cut their false event predictions in half with the help of the machine learning algorithm.

True Positives (TP): Successfully predicted an event. These are the most important measures because this is what will help care workers prevent hospital readmissions and emergency room visits.

False Positives (FP): Predicted an event when an event wasn't occurring. This causes stress for the patient and results in costs for the agency. Over-diagnosed.

True Negatives (TN): Successfully predicted that an event wasn't occuring.

False Negatives (FN): Represent the events missed. It goes without saying that minimizing this number as much as possible is imperative in order to prevent patients from being readmitted to the hospital or having to visit the emergency room.

Performance Results

Figure 2 - Care Worker Performance Results

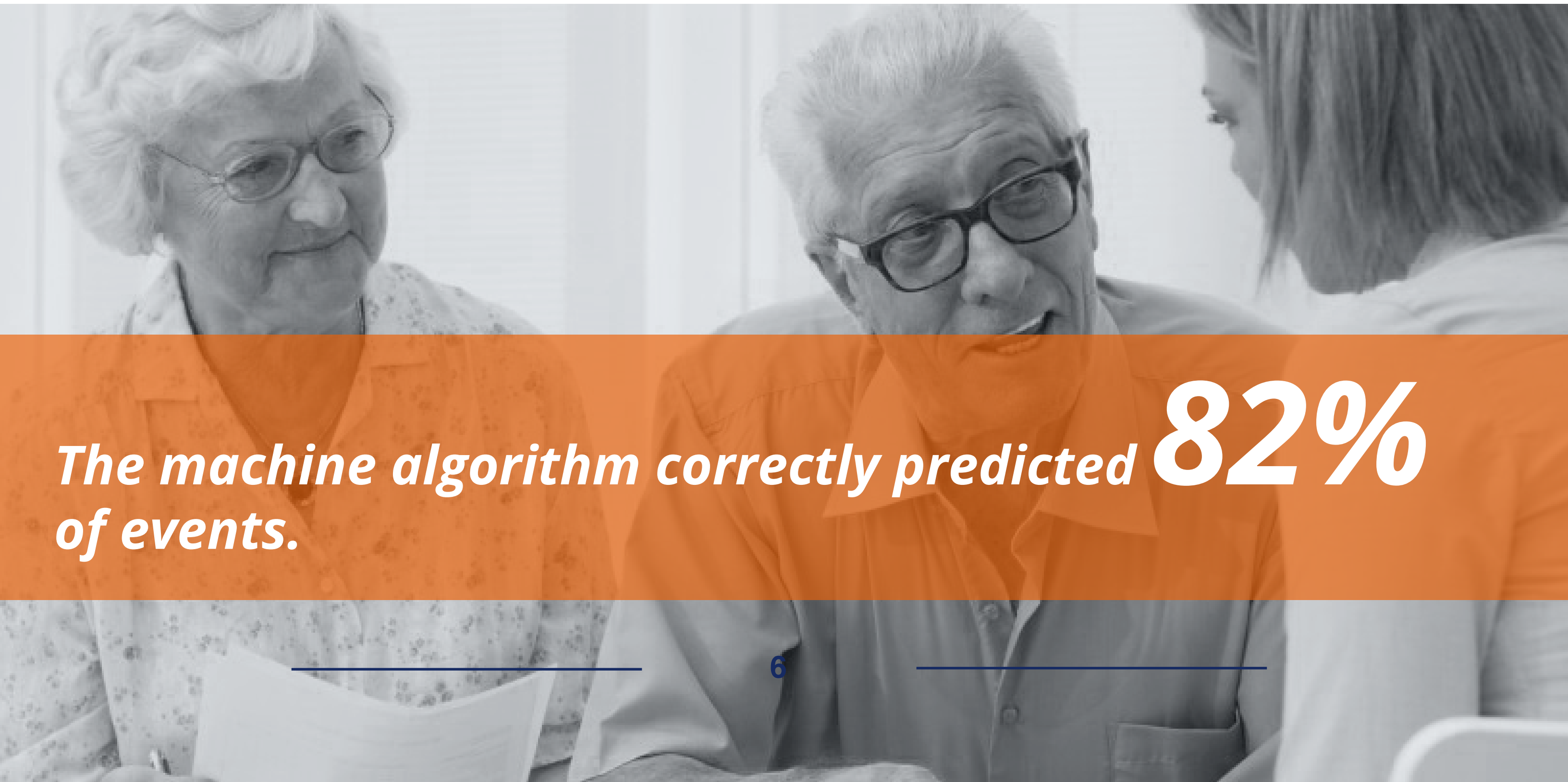
	True Positives	False Positives	True Negatives	False Negatives	Sensitivity	Specificity	SBM
Low Alerts	240	40,080	35,832	207	54%	47%	1.01
Medium Alerts	126	18,847	57,065	321	28%	75%	1.03
High Alerts	109	12,197	63,715	338	24%	84%	1.08
All Alerts	340	54,384	21,528	107	76%	28%	1.04

The care worker alerts were separated into low, medium and high categories with associated manually created thresholds. By using all alerts to predict a day leading to an event, the manual alerts were able to identify 340 of the 457 events present in the dataset, while making false event predictions 54,384 times.

Figure 3 - Machine Learning Performance Results

	True Positives	False Positives	True Negatives	False Negatives	Sensitivity	Specificity	SBM
Machine Learning	376	25,006	50,906	71	84%	67%	1.51

Care workers were able to predict significantly more events with the help of the machine learning algorithm. This shows that the algorithm was able to predict 376 events out of the 457 with only 25,006 false positives; close to half the errors made by the manually setup alerts.



Financial Impacts

Based on the sample population of 210 clients on the Re-ACT program from September 2008 to December 2010, and not accounting for the reduction of false positives, the additional prevented events based on machine learning increased the total savings after the Re-ACT program by $67,298.

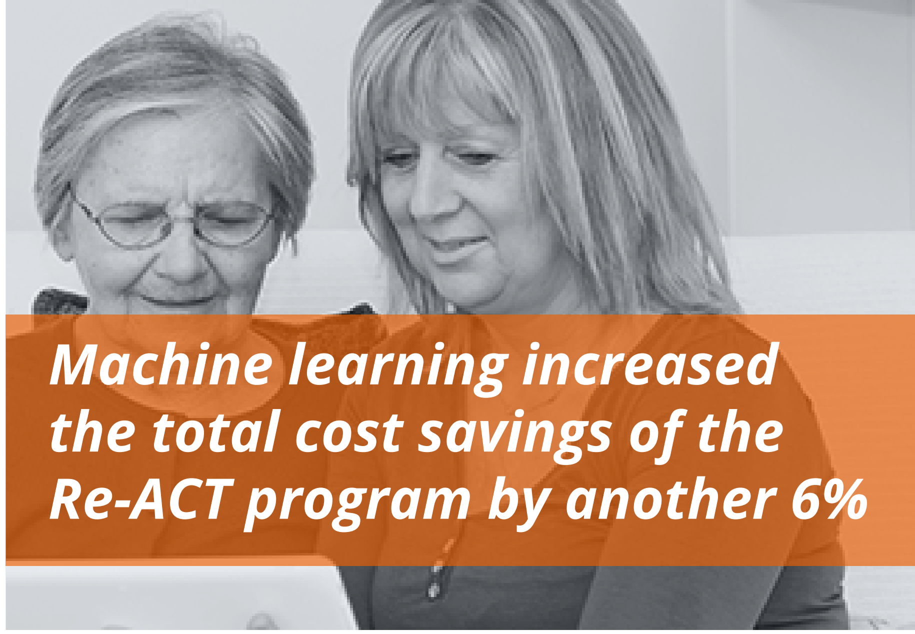


Figure 4 - Re-ACT Financial Savings

	Before Re-ACT	After-Re-ACT	Saving	Machine Learning Potential Saving
FALL PREVENTION				
Rate of falls in Re-act sample	18%	10%	-8%	0%
Cost per fall	$8,666	$8,666	$8,666	$8,666
Total	$321,148	$183,513	$137,635	$137,635
ER VISITS				
Rate of ER visits in Re-ACT sample	64%	30%	-35%	-44%
Cost per ER visit	$138	$138	$138	$138
Total cost	$18,652	$8,626	$10,026	$12,884
HOSPITAL ADMISSIONS				
Rate of hospital stays in Re-ACT sample	35%	19%	-16%	-23%
Cost per hospital stay ($532/day, 9 days stay)	$4,788	$4,788	$4,788	$4,788
Total	$349,231	$186,631	$162,600	$227,040
ALC PREVENTION				
% of clients maintained in home vs Aletrnative Level of Care (ALC)	80%	97%	17%	0%
Cost per ALC ($536/day for 40 day stay)	$21,400	$21,400	$21,400	$21,400
Total	$900,480	$135,072	$765,408	$765,408

**see We Care Re-ACT white paper for expanded cost savings breakdown*

Conclusion

Machine learning, combined with the dramatic increase in the availability and volume of data collected, has the ability to transform the home health care industry. This trend has the potential to become a fundamental decision-support tool for care workers on a routine basis, helping to maximize efficiencies and minimize overall costs. Based on the analysis of the study results, machine learning has the potential to have the following implications on home health care:

- **Care workers could prevent more than 10% of hospital readmissions and ER visits than they would have without the algorithms in place.**
- **Patients could spend more time at home with the help of machine learning algorithms.**
- **Machine learning could reduce the amount of false positives, in turn reducing patient stress levels and the amount of unnecessary procedures.**
- **Efficiencies have the potential to be maximized: care workers could prioritize their time based on the urgency of patients needs.**
- **Machine learning could significantly reduce the overall cost of care due to the potential decline in unnecessary hospitalization and re-admissions.**

As more data becomes available, algorithms will be able to learn more complex patterns and continuously improve their predictions. This trend provides the potential to discover more techniques to continue improving the treatment of patients with chronic conditions.

Works Cited

Health Council of Canada. (2008). Fixing the foundation: An update on primary health care and home care renewal in Canada. Toronto: Author.

Home care in Canada: From the margins to the mainstream. Canadian Healthcare Association= Association canadienne des soins de santé, 2009.

Ward, Brian W., Jeannine S. Schiller, and Richard A. Goodman. "Peer Reviewed: Multiple Chronic Conditions Among US Adults: A 2012 Update."Preventing chronic disease 11 (2014).

We Care. (2011). The Re-Act Program: Remote Access to Care Technology. Toronto.

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